Asset Risk Management for Electric Power Grids

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This is to certify that the thesis prepared

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complied with the regulations of the University and meets with the accepted standards with respect to originality and quality.

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ABSTRACT

Asset Risk Management for Electric Power Grids

Niloufar Youssefi

Civil Infrastructure is essential for the quality of life in developed and developing countries. Since electric power supply is needed for the operation of other vital infrastructure, it is ranked as the highest critical infrastructure. There are substantial adverse impacts on society when power grids fail, resulting in interruption and/or degradation of services. Such failure can cause heavy traffic congestions resulting from nonfunctioning traffic lights, and disturbances for other critical infrastructure elements such as water and sewage treatment plants.

In order to ensure reliability of the bulk power system (BPS) in North America, the North American Electric Reliability Corporation (NERC) requires that power companies submit reports when sufficiently enormous instabilities happen within their territories in order to share the experiences and lessons learned, and to suggest solutions that utilities can apply to their procedures during unusual situations. To simplify and organize information, the NERC has divided the BPS of North America into eight zones, three of which consist of both US states and Canadian provinces. The research presented here focuses on the Canadian part of NPCC zone which covers Quebec, Ontario, New Brunswick and Nova Scotia.

The main purpose of this research is to identify factors affecting power outages in the eastern Canada and develop a model for predicting the likelihood of power outage occurrences based on weather forecasted data. For this reason, System Disturbances Reports from 1992 to 2009 have been scrutinized to determine the conditions in which an attack on power grids can likely happen. According to these reports, various reasons were found to trigger power

outages, including equipment failure, voltage reduction, human error, etc. However, weather conditions are the paramount cause of unavailability of power service in the northeastern district. Weather conditions variables such as wind speed, temperature, humidity, precipitation and lightning are obtained for those same periods from the Environment Canada database. In addition, in two other variables (i.e. electric consumption index and electric network size) are considered as the factors that are likely to impact power outage incidents indirectly.

Based on historical data gathered for weather conditions and power outages, different types of Artificial Neural Network models (i.e. BPNN, GRNN, and PNN) were studied and developed to predict the likely occurrence of power outage utilizing weather forecasted data for four eastern Canadian provinces. Two types of datasets are used for training the models: Dataset I considers the extreme values for all the weather variables, and Dataset II, which consists the extreme value for wind speed (the most critical factor affecting the power grids) plus the values of the other weather variables at the same time that the wind speed reached its maximum value. The results indicate that the best performing model is PNN that was trained with Dataset I for it provides more accurate results. The model is also trained using Quebec dataset, which indicates that data for a specific location is expected to lead to better results. Social cost for electric power outage are then estimated four sectors; residential, commercial, industrial and agriculture.

As a result, once the average duration of power outage is recognized as well as its likelihood of occurrence, the social cost of that power failure could be estimated in the four sectors. The present research helps power companies to predict the likelihood of electric power outage based on weather forecasting data. Furthermore, they are able to estimate the social cost of electric power failure in advance. This will provide useful information for further actions in risk mitigation, and will aide professionalisms in the process of creating choices to improve opportunities and to lessen threats.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R	Regression
NERC	North American Electric Reliability Corporation
NPCC	Northeast Power Coordinating Council
AI	Artificial Intelligence
DUE	Distribution Utility Enterprise
NSERC	Natural Sciences and Engineering Research Council
VoLL	Value of Lost Load
BPS	Bulk Power System
SIC	Standard Industrial Classification

CHAPTER 1: INTRODUCTION

1.1 GENERAL

Electricity is a critical service to so many aspects of contemporary daily lives. It delivers power to a nation's critical military facilities, makes hospitals operable, allows gas stations to function, and keeps the lights on in residence and business (Chertoff, 2014). The electrical power network is an interconnected network made of transmission and distribution lines, which transfer generated high voltage power electricity to the district's center to get delivered to customers through a distribution system (Brown R. , Electric power distribution reliability, 2008; Ward, 2013). The electricity network has created the biggest consumer market in the world. During the past decades, the North American power infrastructure has advanced into what numerous specialists consider the biggest and most complex arrangement of the technological age. This power grid shapes a system of more than 10^6 km of high voltage lines that are consistently directed by modern control equipment, the magnitude of which is unprecedented (Albert, 2004; NERC, 1998). For this reason, the failure of one part of the network can have devastating collateral and cascading effects across a wide range of physical, economic, and social systems. A blackout refers to any aggregate loss of power in a region that results in multiple involuntary customer interruption and lasts more than five minutes. In a case of a blackout, there are expected side effects impacting society. The August 14, 2003, blackout resulted in significant direct financial expenses; insurance companies outlined that approximately $3 billion in claims were submitted to them (Treaster, 2004). Additionally, it resulted in significant nonfinancial losses, for example, subway passengers were stranded underground and emergency vehicles were stalled in traffic due to failed traffic lights (Chertoff, 2014). Asset management is the process of increasing economic benefits and managing the risks and costs over in entire life cycle. The electric power industry is an open competitive market that must management its products and new standards to deliver energy to its customers. Asset management within a power distribution utility enterprise (DUE) involves making decisions to allow the network business to maximize long-term profits, while delivering high levels of service to the customers with acceptable and manageable risks (Tor & Shahidpour, 2006). Disturbances recorded in the NERC records consist of a wide variety of triggering events, including natural disasters (e.g., ice storms, lightning, wind or rain storms), human error (e.g., operator errors), and mechanical failure (Hines P. , 2008). The electrical grid system includes many components that are vulnerable to weather conditions and may experience errors as a result of weather events. This research focuses on weather conditions that may cause unreliability in an electrical network and aims to develop a model to predict the probability of future power outages based on weather forecasting data. Furthermore, social costs, which are consequences of power outages, are estimated for four sectors of residential, industrial, commercial and agriculture.

1.2 PROBLEM STATEMENT

Economic prosperity, national security, and public health and safety cannot be attained without the continuous, reliable operation of electric power grids. The August 14, 2003, blackout in northeastern North America lead to significant direct financial expenses; according to reports provided by insurance companies, they received about $3 billion in claims as result of this blackout (Treaster, 2004). This research is mainly motivated by the consequences on society of power outages. Predicting power outage incidents in advance can reduce financial expenses and increase public safety and wellbeing. The limitations and drawbacks of the current situation can be summarized as follows:

1) All the organizations that are responsible for the reliability of the bulk power system in North America work in some limited common zones in the United States and Canada. Moreover, previous researches have focused on a specific state or area in the United States. There is no research considering the special weather conditions in Canada or developing a model specifically for Canadian provinces, where the weather conditions especially in the winter are more critical.

2) Previous researches have focused on one or two weather variables (e.g., rainfall, tornadoes) and determined their effect on the power grids; none of these researches have considered all the main weather factors in one model.

3) Most of the previous researches only considered big blackouts and focused on the reasons for and causes of each incident. There are few investigations of small power outages and their consequences over a long historical period.

1.3 RESEARCH OBJECTIVES

With respect to the mentioned problems, the overall objective of this research is to develop an intelligent system for estimating the probability of a power outage based on weather conditions and factors. This research seeks to enable electrical companies to determine the possibility of a power outage based on the weather forecasting data. The sub-objectives of this research are the following:

1) Perform a comprehensive literature review on power grids and the generation, transmission, and distribution of electricity power and the social cost of power outages;

2) Identify the probable risks that can threaten the power network and determine the main sources of blackouts on power grids;
3) Develop a model to predict the likelihood of a power failure occurrences based on weather variables and indirect, related variables;
4) Develop a model that specifically considers the weather conditions of eastern Canada, especially winter circumstances;
5) Update and adjust the social cost of power outages in different sectors from previous researches to nowadays electricity consumption price and life style.
6) Estimate the social cost of electric power outage in residential, commercial, industrial and agriculture sectors, based on the average duration of power outage

1.4 RESEARCH FRAMEWORK OVERVIEW

The proposed research framework consists of four computational models, as shown in Figure 1-1 and described below:

1) Literature Review: The literature review encompasses subjects including the state of the electrical power grid (i.e., how electricity is generated, transmitted from the sources to the cities, and distributed to customers), the social costs of power outages (i.e., power outages result in direct economic costs and there are also financial measures of the resulting societal losses), the types of risks for power grids (e.g., natural disasters, ice storms, lightning, wind or rain storms), human error related to power outages (e.g., operator errors and mechanical failure), existing researches that have been done about the failure of power grids and their limitations, asset management of power grids and risk assessment for them, and features and types of artificial neural networks.

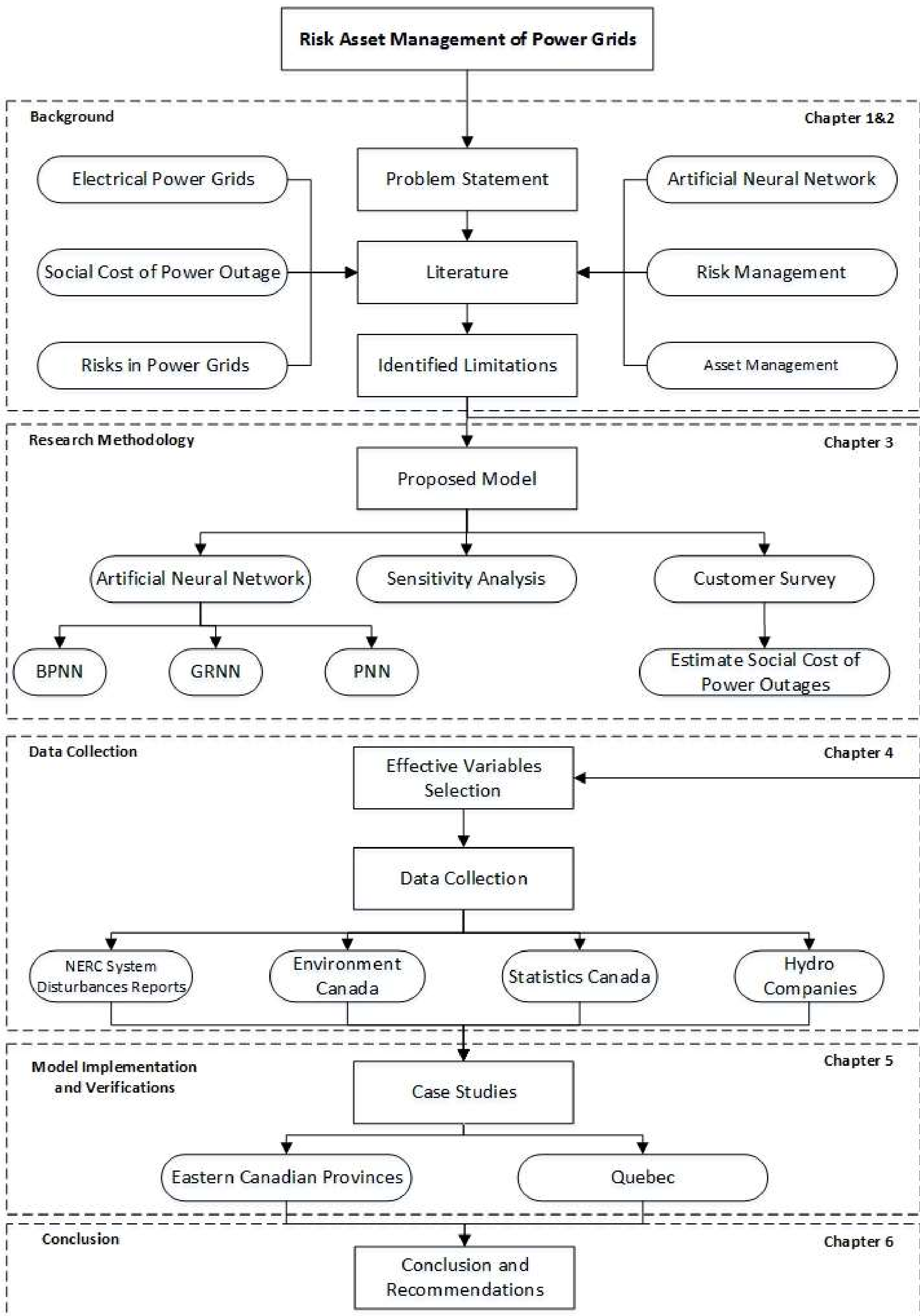

Figure 1-1. Research Framework Overview

2) Research Methodology: Six models were proposed and developed to address the problems identified in the literature and estimate the likelihood of electric power failure occurrences. The model development consisted of five main sub-phases. The first phase trained a BPNN model; once the model was valid, the sensitivity analysis was accomplished in the second phase to find the most critical variables. In the third phase, another BPNN model was trained with a new set of data based on the sensitivity analysis. The fourth and fifth phases involved the training of GRNN and PNN models with the two sets of data, and finally a comparison among the models was developed. Methods for estimating the social cost of power outages were also described.

3) Data Collection: System disturbance reports provided by NERC from 1992 to 2009 were studied to check the reasons for power outage events during these periods. Information about the time, size, location, and cause of power outages in the eastern Canadian provinces were gathered through these reports. The value for identified effective factors are collected as well as social cost of power outages in Canada.

4) Model Development and Implementation: The methodology proposed above was implemented and applied to the case studies in order to verify the developed model. The first case study covered information of four eastern Canadian provinces (i.e., Quebec, Ontario, New Brunswick, and Nova Scotia), and the second case study only covered Quebec. Furthermore, the social cost of electric power outage for two months (January and June) in Quebec are estimated in four sectors; i.e. residential, commercial, industrial and agriculture.

5) Conclusion and Results: Summary of the research and its conclusion is provided in this

chapter. The case studies' data were implemented in the six models and their results were compared to determine the best performing model. Moreover, a general estimation about social cost based on power outage in Quebec is provided. Research contributions and limitation are explained, as well as future works to this research.

1.5 THESIS ORGANIZATION

The thesis consists of six chapters and four appendices. The literature review is presented in Chapter 2. The review covers the topics of general information about the electrical power grid, the social cost of power outages, types of risk for power grids, existing works about power outages, asset management, risk assessment and artificial neural networks. Chapter 3 begins by presenting an overview of the research methodology and then provides a comprehensive description of the proposed framework. Chapter 4 introduces the case study and presents the data collection source, procedure, and preparation. Chapter 5 reviews the results of implementing the proposed model in the two case studies and highlights the merits of the proposed framework over other systems, in addition social cost for likely power outage is also estimated. Chapter 6 outlines the conclusions of the research, highlighting the contributions and limitations of the thesis, along with suggested future research work.

CHAPTER 2: LITERATURE REVIEW

2.1 CHAPTER OVERVIEW

This chapter aims at providing a comprehensive literature review about the current state of power outage in bulk power system. Also, the techniques to avoid blackouts incidents to provide a reliable electric power network are overviewed. Figure 2-1 illustrates an overview of this chapter.

Section 2.2 reviews the literature related to electrical power grids, and how electricity is generated, transmitted from the sources to the cities, and distributed to customers. Section 2.3 is related to the social cost of power outage. This section provides information about the side effects of power outage in society and how it can influence people life. Section 2.4 focuses on the literature related to the risks that can increase the probability of power outage, e.g., natural disasters, ice storms, lightning, wind or rain storms, human error and mechanical failure. Section 2.5 describes asset management concept and it continues giving information about risk management and assessment management of power distribution utilities enterprises. Section 2.6 focuses on the literature related to artificial neural network including three subsections, namely, BPNN, GRNN, and PNN. The literature regarding sensitivity analysis techniques is summarized in section 2.7. And finally, summary and identified the shortcomings of the reviewed literature will be presented in Section 2.8 and 2.9.

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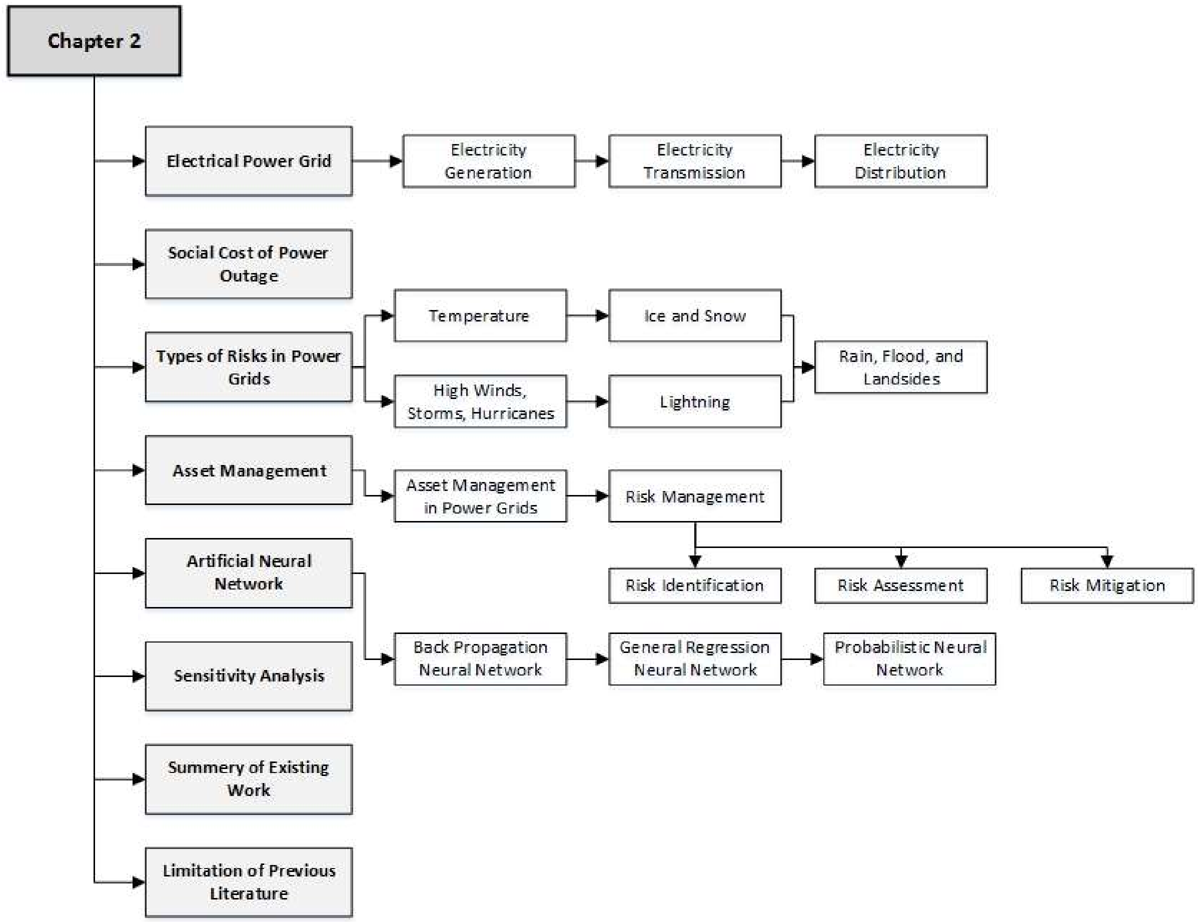

Figure 2-1. Chapter 2 Overview

2.2 ELECTRICAL POWER GRIDS

It's been more than several decades that human have known about electrical phenomena. Nowadays, a reliable electricity supply is an essential resource for modern life. Electricity is produced and delivered from supplier to customer through generation, transmission and distribution systems. Electrical power network is an interconnected network made of transmission and distribution lines, which high voltage power transfer generated electricity to district's center to get delivered to customers through distribution system (Brown R. E., 2008; Ward, 2013)

Electricity network has created the biggest consumer market in the world. During the past decades the North American power infrastructure has advanced into what numerous specialists consider the biggest and most complex arrangement of the technological age. This power grid shapes a system of more than 10^6 km of high voltage lines that are consistently directed by modern control equipment, which make it unprecedented magnitudes network (Albert, 2004; NERC, 1998). Following paragraphs provide a brief description of different stages in electrical power stages.

2.2.1 Electric Power Generation

Electricity power is generated in power stations, which work by dynamic energy of flowing water and wind or the power of heat engines fueled nuclear fission or chemical ignition. Moreover, solar photovoltaic and geothermal power are able to play a significant role in power generation technology (Bayliss, 2012).

Canada has had a significant role in modernization and development of natural resources in the service of electricity production by establishing the first hydroelectric generating station at Chaudière Falls in 1886 in Ottawa. There are many resources of energy existing in Canada such as hydroelectric, coal, oil, gas, uranium, wind, and biomass. Choosing the best resources depends on the availability, suitability and possibility of various technologies in different districts (Canadian Electricity Association, 2006). Figure 2-2 shows current power generation sources by provinces.

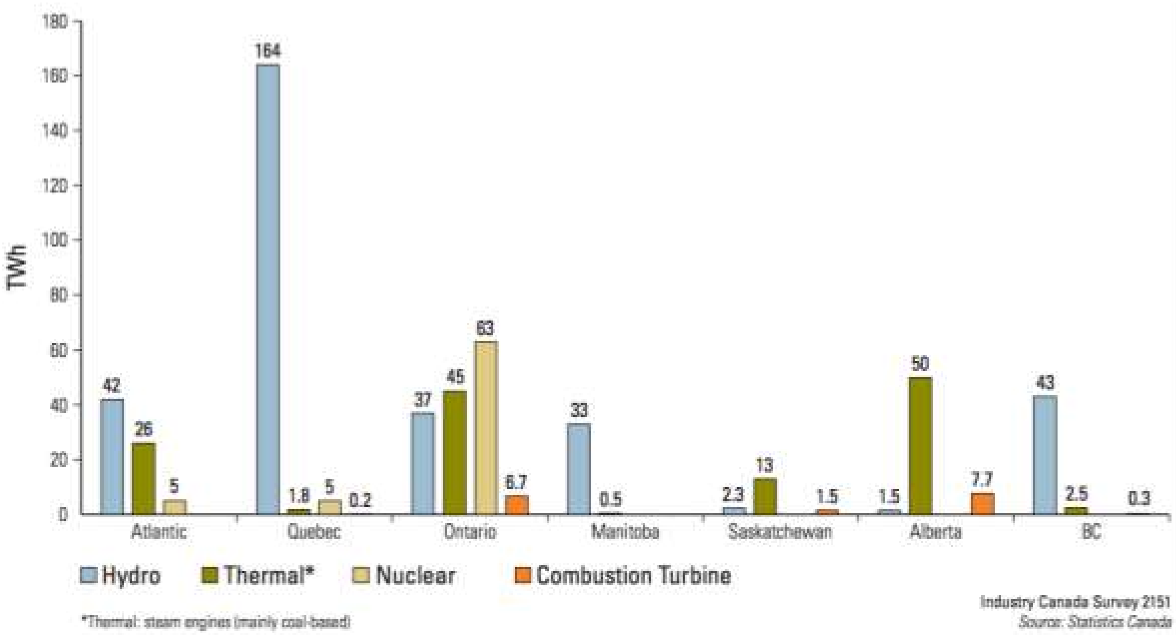

Figure 2-2. Current Power Generation Sources by Provinces (Canadian Electricity Association, 2006)

As it was shown in Figure 2-2, Over 99% of Quebec's output comes from renewable energy sources. Producing power in a sustainable manner aids to save the nature for future generations. Quebec long ago settled on hydroelectricity, a clean, renewable energy source with known, well-controlled environmental impacts, which empowers Quebec to post one of the lowest greenhouse gas emission rates per capita in North America (Hydro Quebec, Annual Report , 2014)

2.2.2 Electric Power Transmission

After electricity is generated, transformers, showing in Figure 2-3, increase its voltage and it is then delivered to local distribution centers through bulk transmission lines. There are two systems by which high voltage can be transmitted:

- High voltage Direct Current (DC)

- High voltage Alternating Current (AC)

DC systems is able to cover customers within about 2.5 kilometers from the sources while there is no limitation in AC systems; consequently most transmission lines are high-voltage AC. Also, maintenance of AC substation is quite easier and more economical compared to DC system (Bayliss, 2012; Hydro Quebec, Annual Report , 2014)

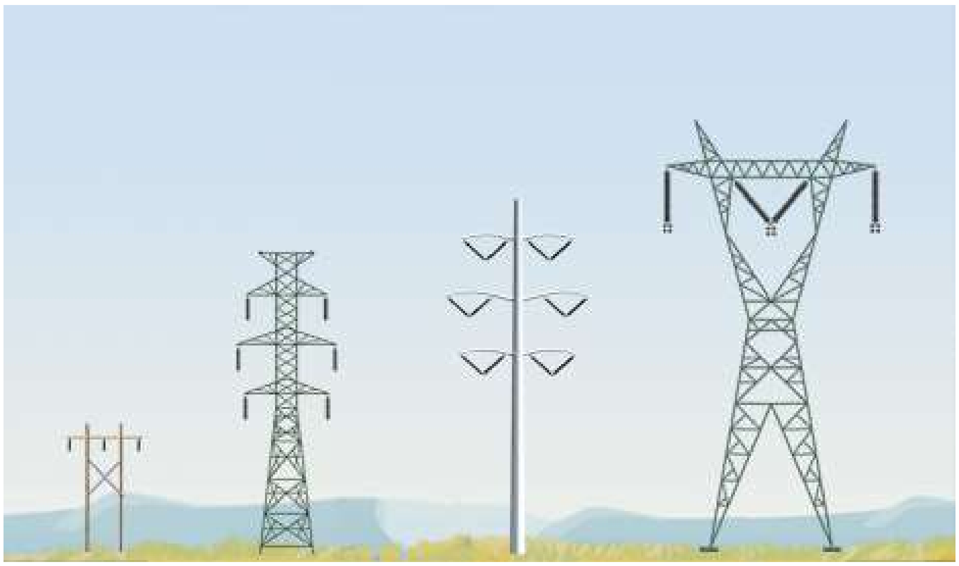

Figure 2-3.Transmissions to Transmit Electricity between 44 kV and 765 kV (Hydro Quebec, Vegetation and safety near transmission lines, 2015)

2.2.3 Electric Power Distribution

Electric power distribution is the distinct between the local wiring and high voltage substations i.e. the last phase in the delivery of electric power to individual customers. Distribution substations bring down the transmission voltage to medium voltage to be carried to distribution transformers located near the customer's locations. Transformers again lower the voltage to the use voltage of family unit machines (Ward, 2013).

2.3 SOCIAL COST FOR POWER OUTAGE

As the power grid grows in size, becomes more complex, as a result, recognizing the emergent behaviors that can happen in the system becomes more Important (Albert, 2004). Economic prosperity, national security, and public health and safety cannot be attained without the continuous reliable operation of electric power grids (Ouyang, 2011). A blackout refers to any aggregate loss of power in a region that results in multiple involuntary customer interruption and lasts more than five minutes. Outages durations depend on nature of the blackout and the arrangement of the electrical systems (Zhang, 2010).

In a case of blackout, there are expected to be side effects impacting the society. It is valuable to make an interpretation of blackout sizes into some measure of social cost, which incorporates direct economic costs and a financial measure of societal losses (Hines P. , 2008). The August 14, 2003 blackout accompanied with significant direct financial expenses; according to insurance companies, there were about $3 billion claims submitted to them (Treaster, 2004). Additionally, it resulted in big non-financial losses, for example, subway passengers stranded underground and emergency vehicles stalled in traffic due to failed traffic lights.

The social expenses of a power outage are a component of many elements including the size of the blackout, the length of time of the blackout, its location and the time of day. Obviously power outage expenses grow with the geographic extent of the event. Mega Watt (MW), Mega Watt-Hour (MWh), or number of customers affected by power outage usually measures size of a blackout. Table 2-1 summarizes three examples of blackouts in North America in 1965, 1996 and 2003. The primary disturbances that triggered incidence of blackouts are variable, such as natural disasters, human error, and mechanical failure (Zhang, 2010).

Table 2-1 Some Notable Cascading Failures in North America (Zhang, 2010).

Date	Location	Size	Initial Reason	Critical Events
11-09-1965	Northeast US	30,000,000 people	Maintenance person incorrectly set a protective relay to trip too low on one of the transmission lines between the Niagara generation stations Sir Adam Beck Station No.2 in Queenston, Ontario.	Two generators with no outlet for their power were automatically shut down to prevent damage. Within five minutes the power distribution system in the northeast was in chaos as the effects of overloads and loss of generating capacity cascaded through the networks.
07-02-1996	Western North America	55,000,000 people	3:42 pm, a 500 kV line sagged into a tree. 3:47 pm another line shorted out. 3:48 pm, the 13 turbines at McNary Dam tripped off line.	
08-14-2003	Northeast US, Canada	50,000,000 people / 57669 MW	2:02 pm the first 345 kV transmission line sagged into a tree initiated the blackouts.	256 power plants are off-line, 85% of which went off-line after 4pm, most due to the action of automatic protective controls.

Lawton (2003) in a study of 24,800 customers outages, found that commercial and industry customer costs growth did not have a linear relation with outage duration, i.e. per kWh blackout costs increased over the first 9 hours and then decreased. In another example, Lawton claims that a blackout that cause dysfunction in all of the traffic lights in a whole city for 1 hour would probably be more costly than 2 blackouts that disabled 1/2 of the city's traffic lights each for 1 hour. The larger blackout might remove all alternate paths for traffic, and cause a much larger traffic problem (Billinton, 2001; R. Billinton J. O., 1987; R. Billinton R. A., 1996).

There are three methods that are employed in literature to estimate the cost of electricity power outage; production function approach, customer survey and case study (Linares & Rey, 2012).

Linares and Rey (2012) investigated the costs of electricity interruptions in Spain using the production function approach. This method counts the amount of consumed electricity power and its generation value it to estimate the costs of electricity interruptions. The value of one unit of electricity, is known as the Value of Lost Load (VoLL).

De Nooji, Koopmans & Bijvoet (2007) and Leahy and Tol (2011) used the production function approach to estimate the VoLL in the Netherlands and Ireland respectively. De Nooji, Koopmans & Bijvoet (2007) found that in 2001 the cost of 1 kWh of electricity supplied in the Netherlands was about €8.56. The results indicated that an electricity interruption cost for different sectors would be different. For example the cost of electricity interruption in construction sector would be around €33/kWh; while in manufacturing would be €1.87/kWh. Leahy and Tol (2011) found that in 2008 the average cost of electricity interruptions in Ireland, was €12.9/kWh. They also found that the VoLL for households (€24.6/kWh) is higher than in the industrial sector (€4/kWh).

However, customer surveys are mostly used in the studies which estimate the cost of power interruptions. In surveys, people are asked about the cost of an interruption (as a function of duration) and interruption costs are usually expressed in terms of the load disconnected (€/kW). Wacker and Tollefson (1994) used the survey method to find the customer costs of electric power system interruption in Canada. Their studies for Natural Sciences and Engineering Research Council (NSERC) was in conjunction with eight Canadian electrical utilities. The results illustrate the customers' experiments about electricity interruption and its impact on their activities their and the associated costs.

Balducci, Roop, Schienbein, DeSteese, & Weimar (2002) used survey data collected by the University of Saskatchewan in 1992 and 1996 to estimate interruption costs in U.S. They found that in 1996 the average cost of an hour interruption in U.S. economy was $8.76/kW. Interruption costs for the transport sector was $16.42/kW per hour, while the cost for households was $0.15/kW. One hour interruption cost in Canada for three sectors were estimated by Billinton (2001). The author's research was based on the the data collected by the University of Saskatchewan and results shows that the interruption cost for industrial is (C$5.19/kW), for commercial is (C$32.20/kW) and residential is (C$0.31/kW). Table 2-2 summarizes the literature works conducted to find the social costs of the outage of transmission line at different countries.

Table 2-2. Summary of Interruption Cost Studies (Linares & Rey, 2012)

Author	**Country**	**Year**	**Methodology**	**Total estimated cost**
Targosz and Manson (2007)	Europe-25	2004-2006	Surveys	$ 150 Billion Annually
LaCommare and Eto (2006)	US	2011	Surveys	$ 79 Billion Annually
EPRI (2001)	US	2001	Surveys	$ 47 Billion Annually
Nooij et al (2006)	Netherland	2001	Production Function	€ 8.56/kWh
Leahy and Tol (2010)	Ireland	2007	Production Function	€ 12.9/kWh
Balducci et al (2002)	US	1996	Surveys	$ 8.76/kW (1 hour)
Billinton (2001)	Canada	1996	Surveys	$ 12.00/kW (1 hour)
Trengereid (2003)	Norway	2001-2002	Surveys	€ 25.2/kWh
Bertazzi et al(2005)	Italy	2013	Surveys	€ 32.4/kWh

2.4 TYPES OF RISKS IN POWER GRIDS

In 2012, the Edison Electric Institute sought to proactively and systematically identify threats that, if successful, would result in major consequences and interrupt electric companies' ability to generate, transmit, and distribute power. A wide range of potential threats is shown in Figure 2-4. Risk in Power Grid Landscape (Chertoff, 2014)

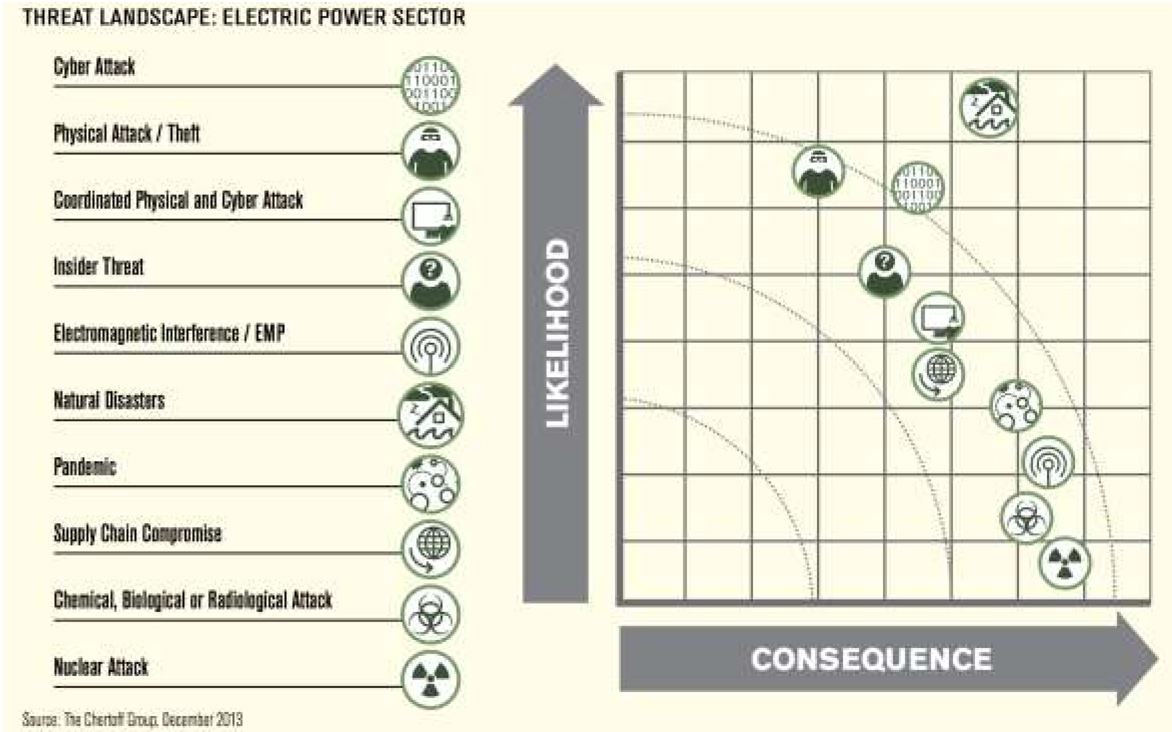

Figure 2-4. Risk in Power Grid Landscape (Chertoff, 2014)

As indicated in Figure 2-4, these threats range from those of high likelihood with significant consequences should they occur (such as natural disasters) to lesser likelihood with severe consequences (such as nuclear, chemical biological, or radiological attacks) (Chertoff, 2014). Although all high-voltage transformers are designed to survive from operational risks such as lightning strikes and hurricanes, utilities frequently experience damage to high-voltage transmission towers due to both weather and malicious activities (Parfomak, 2014). This research focuses on natural disasters and weather conditions that may cause both physical destruction like equipment failure and a raise in public consumption. Following paragraphs review the effects of weather events on grid systems.

2.4.1 Temperature Effects

As the temperature increases the demand for electricity is expected to raise, as well as electricity generation pattern, as a result equipment may not be able to bear maximum power rating surge, and probability of energy losses increases (Ward, 2013).

For safety issues, there must be a safe distance below the sag on the conductor line and trees. If there would not be a safe distance, on hot days, as the temperature of the lines grows, the risk of multiple flashover faults to the trees will increase (Bayliss, 2012; Brown R. E., 2002). This was partly the initiating cause of the major USA-Canada blackout in 2003 (U.S.-Canada Power System Outage Task Force, 2004). The best way to avoid this kind of problems is to make sure about adequate cutting of trees growing below overhead lines.

2.4.2 High Winds, Storms, Hurricanes

High winds can cause faults and harm to overhead power lines, by being blown against the lines, trees being blown over onto the lines and finally utility poles being blown over or transmission towers failure in extremely high winds (Ward, 2013).

According to Hines & Talukdar (2009), study about major blackouts in North America indicates that wind, storm, hurricane or tornado has a main impact of loss of power outage occurrences. General conclusion about from previous works (Ward, 2013; Davidson, 2003; Winkler, 2010; Reed, 2008) show that:

- Distribution networks are more sensitive against the hurricanes and storms than transmission network
- Trees are the main reason of damage to distribution networks;
- Damages are caused in the same time as the wind reaches its maximum;

- There are some examples of significant damage to transmission network while the storm was so severe.

2.4.3 Ice and Snow

Heavy snow increases the weight of conductor lines and makes them more venerable against high winds. Also the weight of snow on trees can also cause them to fall and damage lines. When super-cooled rain is mixed with strong wind, it will freeze as quickly as it contacts trees and overhead lines, thick layer of ice is made. This event is called “ice storm”, which in January 1998 happened in Canada and North East USA, and destroyed a big number of transmission towers and about two million consumers were affected (Electric Power Research Institute (EPRI), 1998; North American Electric Reliability Council (NERC), 2001).

In cold countries like Canada, the transmission towers and lines are designed for the maximum expected ice and wind loading, but sometimes this is not enough. In the 1998 Canadian event, ice reached a thickness of 70–90 mm on overhead lines. The Ontario Hydro design was for 25 mm of ice on 230 kV and 115 kV lines and 50 mm on 500 kV lines, while the requirement of the Canadian Standards Association was for only 12.5 mm of ice (Eurelectric, 2006).

2.4.4 Lightning

Lightning strikes on or near conductor line can cause flashover (short-circuit), which make disturbances in electrical supply network. Normally, such faults fixed by de-energizing the circuit, yet, the voltage wave caused by the lightning strike may travel along the lines and cause damage to equipment such as transformer windings (Ward, 2013).

EPRI (2006a) claims that lightning strikes are the most common cause of transmission line outages in the USA, and also the NERC's system disturbances reports, which are considered in this research, confirm this theory in Canada eastern provinces. However, Hines & Talukdar (2009) in their analysis of major loss-of-supply events suggests that lightning was the principal cause of only 8% of the events.

Although thunderstorms with lightning are not happening all over the USA, and in some places such as Florida and the Gulf Coast are most common, EPRI (2006a) has assessed that the direct cost to utilities in the USA of damaged or destroyed equipment due to lightning is around $1 billion per year.

There are some ways improved to protect the power network against lightning strikes by Bayliss (2012), EPRI (2006a) and (Institute of Electrical and Electronics Engineer, 1997). They suggest to add an earth wire above the live conductors on distribution circuits, or to add an earthed bonding wire to wooden poles, or using better surge arresters.

2.4.5 Rain, Flood, and Landsides

Very heavy rain rarely causes flashover faults (short-circuits) across insulator. However, heavy rain is normally associated with strong winds or lightning, which are more likely to cause faults than the rain (Ward, 2013).

Heavy rain may cause flooding and landslides. Floods near the coast not only are accompanied with storms and high winds, but also as the water level increases, it can ingresses to equipment such as switchgear, transformers and control cubicles mounted at ground level in substations (e.g., Hurricane Katrina in 2005). If such equipment is damaged by water, it is probable to take many weeks to repair or replace. To keep power installations safe against flooding or landsides, new equipment must not be located in the areas that are at risk. For existing ones in a flood risk area necessary flood defenses need to be established (Ward, 2013).

2.5 ASSET MANAGEMENT

Asset management is an expression originated from the financial industry that its main concepts are exerted to financial instruments such as investments, bonds, cash, etc. Asset management is the art of adjustment between cost, performance, and risk. Investors recognize a passable risk through asset management methods while the profits are maximized (Brown & Spare, 2004). It involves making decisions to allow the network business to maximize long-term profits, while delivering high service levels to the customers with acceptable and manageable risks (Tor & Shahidpour, 2006).

Normally, companies embrace an asset management approach to either decrease spending more, successfully manage risks, or drive corporate goals through an association (Morton, 1999).

To accomplish a thought out asset management demands the arrangement of corporate goals, management decisions, technical decisions, organizational design, processes, information systems, and corporate culture. Effective implementation can help companies achieve higher level in business achievement but canned approaches are bound to fail (Brown & Spare, 2004).

2.5.1 Asset Management in Power Grids

Asset management within a power Distribution Utility Enterprise (DUE) involves making decisions to allow the network business to maximize long-term profits, while delivering high service levels to the customers with acceptable and manageable risks. The electric power industry is open competitive market with challenges for effective management of its products and standards for delivering energy to customers. Maintaining a reliable facility to ensure sufficient supplies of energy, reserves, voltage support and other basic services at the lowest possible cost to ratepayers are the mission of Power Company's operating personnel (Tor & Shahidpour, 2006)

Experience shows that the coordination of time scales for asset management plays a critical role in strategic decisions. Asset management based on possible time scales is categorized as follows:

- Real-time asset management (online outage management)
- Short-term (one day ahead and weekly) asset management, which encompasses risk-constrained asset valuation
- Midterm (monthly and seasonal) asset management for optimal maintenance scheduling of equipment and optimal allocation of resources (e.g., fuel, emission, and hydro)
- Long-term (yearly and beyond) asset management, which encompasses facility planning and acquisition.

Real-time asset management is critical for maintaining security in competitive power systems. Real-time asset management is associated with unexpected outages of power system components and hourly load fluctuations due to sudden changes in weather conditions. Short-term asset management maximizes the rate of return on asset investments by optimizing the company's portfolio and minimizing asset exposures to financial and physical risks associated with the volatility of hourly prices and customer demand. Midterm asset management is associated with the optimal maintenance scheduling of facilities based on perceived reliability (reliability-centered maintenance), fuel and emission constraints procurement, and natural resource availability (such as water inflows for hydro units). Midterm asset management can be exposed to the financial risks associated with forward electricity and fuel prices. Long-term asset management is associated with the construction and acquisition of generating plants and transmission facilities. The financial risks for the latter are greater than those of the former; construction lead-time, long-term load diversity, and interest rates are some big risk factors of long-term asset management (Shahidehpour & Ferrero, 2005).

2.5.1 Risk Identification

Risk is described as an uncertain event or condition that has both positive and negative outcomes when it is triggered. (Project Management Institute, 2013). It is necessary to use risk management from the early stage of a project, where main judgments and decisions about the project can be impacted such as choice of alignment and selection of construction methods (Eskesen, 2004). Risk management process involves identifying and analyzing risks of the project (Wysocki, 2011).

Risk identification is the principle phase in the risk management process, as it efforts to find the cause and type of risks. It involves the identification of potential risk event conditions in the project and the explanation of risk responsibilities (Wang, 2003). In the other words, Risk identification develops the base for the next stages of analyzing and controlling of identified risks (Carbone & Tippett, 2004). Risk identification is an iterative process because new risks may become known as the project progresses through its life cycle and previously identified risks may drop out (Caltrans Office of Statewide Project Management Improvement, 2007).

2.5.2 Risk Assessment

Risk assessment is the approach to analyze the impact of identified risks on project performance. Generally, there are two types of risk analysis, qualitative risk analysis and quantitative risk analysis.

2.5.2.1 Qualitative Risk Analysis

Qualitative risk analysis is considered as an assessment process, which contains explanation of each risk and measures the priority of identified risks (high/medium/low) by using their relative likelihood of event occurrence, and their corresponding impacts on the project's objectives (Zou, 2007).

2.5.2.2 Quantitative Risk Analysis

Quantitative risk analysis is the procedure of utilizing numerical approaches to analyze the effect of identified risks concerning overall project objects. Typically, quantitative risk analysis is performed when needed after the qualitative risk analysis is being executed.

Quantitative analysis includes more refined strategies and methods to investigate and analyze project risks (Modarres, 2006).

2.5.2.3 Define Risk Value

A simple, but commonly used definition of the risk value is exemplified in equation where P is a number associated with a determined probability category, while C is a number associated with a determined consequence category (Andrews & Moss, 2002).

$$Risk\ Value = P \times C$$

The risk value could then be used as input to decide if and how the risk should be treated (often combined with a cost analysis). This approach has been used by the electric power industry in Sweden, as part of an RCM method (Wallnerström, 2011).

2.5.3 Risk Mitigation

Risk mitigation is the process of creating choices and actions to improve opportunities and to lessen threats to project objects. According to Hillson (1999), risk mitigation and risk response development is often the weakest part of the risk management process. The proper management of risks requires that risks be identified and allotted in a well-defined manner. There are four option strategies to be applied in order to reduce the negative effects of risks on project – risk avoidance, risk transfer, risk mitigation, and risk acceptance. Following are some basic definitions of these strategies:

2.5.3.1 Risk Avoidance

It is a risk response whereby the project team or organization acts to reject the threat or defend the project from its negative effect. By this strategy, the project manager may change the project management plan to eliminate the threat entirely.

2.5.3.2 Risk Transfer

In this strategy, project team shifts the impact of negative risks to a third party through (Wang, 2003):

- Insurance companies;
- Subcontracting to subcontractor;
- Modifying the contract terms and conditions to client or other parties

2.5.3.3 Risk Mitigation

It is the method the project team takes step to reduce the probability and impact of risk. Taking early actions to reduce the probability and impact of a risk is often more effective than trying to repair the damage after the risk has occurred.

2.5.3.4 Risk Acceptance

It is the strategy whereby the project team makes decisions to acknowledge the risk and not take any action unless the risk occurs.

2.5.3.5 Risk Monitoring

Risk monitoring is the procedure of acknowledging risk response plans, recognizing risks, tracking risks, controlling leftover risks, identifying new risks throughout the entire project life. The primary purpose of risk control is to make risk response a continuous process, resulting in an optimum risk response.

Examples like choosing alternative techniques, executing a contingency or fallback plan, taking corrective actions, and modifying the project management plan are involved in the risk control process (Caltrans Office of Statewide Project Management Improvement, 2007)

2.6 ARTIFICIAL NEURAL NETWORK (ANN)

There are various explanations of Artificial Intelligence (AI) in the literature. Following paragraph provides several definitions presented by some researchers:

- "AI goal is to make a replacement of a specific level of human intelligence in a machine" (Brooks, 1991).
- "AI is about making intelligent computers programs to realize human intelligence" (John McCarthy 2007).
- "The art of building a kind of mechanisms and systems to do humans' tasks which need intelligence for performing them" (Kurzweil, 1990).

In general, AI can be briefly described as the approach of understanding and making intelligent systems that exhibit intelligent behavior. The word intelligence covers different skills such as resolve problems, learn, and understand language which AI can state all of those (Engelmore, 1993). Among the common of AI applications and methods, Artificial Neural Networks (ANNs) is one of the most well-known and frequently used one.

ANNs are somehow a basic copy of the neural structure of the brain. Brains store information as patterns. Some of these patterns are very complicated that let us the capability to identify specific data aspects from many different angles. It is a hard task for computers to recognize even simple patterns, generalize them and predict actions of the future based on same pattern. ANN is a mathematical model which finds patterns among the datasets where there are complex relationships between the inputs and outputs, store those patterns, then use them for analyzing and applying solutions for problems (Anderson & McNeill, 1992).

Neuron is the essential processing component of a neural network. Natural neurons obtain inputs, synthesize them and implement a nonlinear process on the result, and then output the final result. ANN tries to simulate the arrangement and process of human neural network system. Artificial neurons are mathematical process, which get a weighted sum of several inputs and passes them through a “transfer function”. **Error! Reference source not found.** indicates a diagram representing an artificial neuron which reflects the most frequently and simplest, type of ANN.

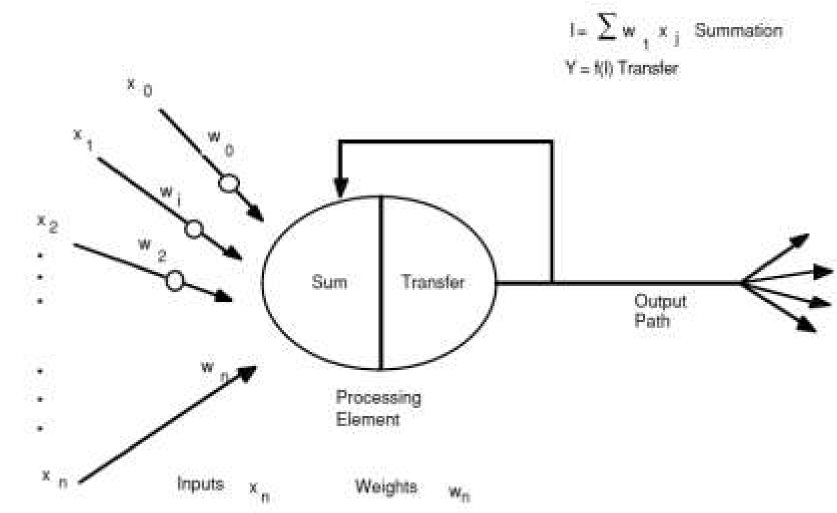

Figure 2-5. A Basic Artificial Neuron (Anderson & McNeill, 1992)

Inputs are shown by the mathematical symbol *x (n)* and weights are represented by *w (n)*. In this structure, the output of each artificial neuron is an input for the others and collectively they build an interconnected net of ANN. Mainly, all artificial neural networks possess a similar anatomy as shown in **Error! Reference source not found.**. In most network applications, artificial neurons comprise three sorts of layers namely, input, hidden, and output layers. The first layer, input layer, collects the data and the last layer, output layer, sends information straightly to the outer world or to a subsidiary computer progress. All of the datasets are deemed as hidden layers, which comprise many neurons. The outputs of input layers are the inputs of hidden neurons, which their outputs are the final layer input (Anderson & McNeill, 1992).

2.6.1 Supervised Training of an ANN

Two different methods are mostly used in literature for training of ANNs: supervised and unsupervised. In the first method, the mechanism involves the network with appropriate output, while unsupervised method some initial conditions are considered on inputs. Literature review indicated that most of the networks are developed based on supervised training method

In supervised training, both the inputs and the outputs are provided, so this is expected to allow the network to compare the outputs coming from training process with the real desired outputs. Weights are usually randomly set to begin the process, and as the training process is repeating continuously, they are more adjusted to make a closer match between the desired and the actual output. Training process keeps modifying the input weights until the system gets into the required point, so it is expected that the ANN is able to forecast the right answer.

To proceed, two types of data are needed; “training set” and “test set”. The set of data, which enables the training as many times as needed, is called the “training set”. To supervise the training, a set of data needs to hold back to be used to test the system, which is called “test set”. Training sets are demanded to include large number of data and also comprise a broad variety of data, which contain the features that the network needs to learn such as relations between the data (Anderson & McNeill, 1992).

2.6.2 ANN Types

There is a similarity among all the ANNs, but different learning rules and their modifications, cause various architecture for the networks and make each of them suitable for a specific application. Basically, most applications of ANNs are divided into five categories:

- Prediction
- Classification
- Data Association
- Data conceptualization
- Data filtering

Table 2-3 indicates a comparison among the network categories, their applications and usage.

Table 2-3. Network Selection Table

Network Type	Networks	Use for Network
Prediction	• Back-Propagation • Delta Bar Delta • Extended Delta Bar Delta • Directed Random Search • Higher order Neural Networks • Self-Organizing Map into Back-Propagation	Use input values to predict some output
Classification	• Learning Vector Quantization • Counter Propagation • Probabilistic Neural Network	Use input values to determine the classification
Data Association	• Hopfield • Boltzmann Machine • Hamming Network • Bidirectional Associative Memory • Spatio-Temporal Pattern Recognition	Like classification but it also recognizes data that contains error
Data Conceptualization	• Adaptive Resonance Network • Self-Organizing Map	Analyze the inputs so that grouping relationships can be inferred

Data Filtering	• Recirculation	Smooth an input signal

This research focuses on three types of "back-propagation neural network" (BPNN), "general regression neural network" (GRNN) and "probabilistic neural network" (PNN). (Anderson & McNeill, 1992).

2.6.3 Back Propagation Neural Network (BPNN)

The main role of networks of predictions is to forecast what is predicted to happen for a project in the future, also it can be useful in setting priorities for a project. Literature review showed that in the early 1970's, BPNN architecture was developed (Parker, 1987; Rumelhart & McClelland, 1986) and is the most popular learning algorithm in all types of ANNs and is used more than all others. The typical BPNN consists of an input layer, an output layer, and at least one hidden layer. The approach in this method has concentrated on developing hidden connection between the input data and output data with using a set of data. To reach this purpose, network compares the actual outputs and desired outputs, and then the difference between them is back propagated to the previous layer(s). BPNN implements two key tasks: (1) learning and (2) recalling (Hegazy and Moselhi 1994). Learning can be defined as process of obtaining appropriate weights and biases of raw data, in order to find the closets outputs based on the defined objectives (Zayed and Halpin 2005). In recalling process, the input data are given to the trained network and the responded outputs are compared with the defined targets. The trained method can be used for any upcoming set of data, in which there is similarity connection between the inputs and output data (Bryson, 1975; Werbos, 1974; Alpaydin, 2014; Rumelhart, 1998).

This technique is very practical in data modeling due to high capability to learn from the examples (Lawrence 1994). This method could be used to develop a model in which the connection between inputs and outputs is vague. Reviewing the existed patterns and relationships throughout the previous data can help to achieve the required knowledge. This knowledge is necessary to defined in order to estimate the unknown output values from a set of input data (Sawhney et al. 2002). Since in process of ANN, it cannot explain the inner reason, it is appropriate more for finding relationships in problems that no reason or numbers of input-output relations can be found (Elwakil 2011).

During last few decades, more researches are focused on applying the ANN in the construction industry. Literature reviewed showed that this technique is used in many aspects on construction management. Some examples projects can be projects' cash flow prediction, risk analysis, resource optimization, and the tendering outcomes prediction (Boussabaine 1996; Li 1995).

Although these limitations exist in applying the ANN, the researchers still prefer to use this network for solving complicated construction management problems (Anderson, D., & McNeill, G. 1992). For instance, Kim, An, , & Kang (2004) used three different models including; Multiple Linear Analysis, ANN and case-based reasoning to estimate the construction cost. The results showed that the ANN can predict the construction cost more precisely than the other two methods. Also, using the BPNN in estimation of the productivity rate of construction trades based on several specific attributes was presented in Moselhi, Hegazy, & Fazio, (1992) research. Zayed & Halpin, (2005) indicated that BPNN technique can use precisely to estimate the productivity, cost and cycle time of the piling process. Hsu, Gupta, & Sorooshian (1995) used BPNN to demonstrate the potential of BPNN models for simulating the nonlinear hydrologic behavior of watersheds.

2.6.4 Probabilistic Neural Network (PNN)

Network for classification is defined when there is an object requiring to be related to a class. This relation is based on number of observed aspects corresponding to an object. An example of implementing clarification is power outage problem outage (Zhang G. , 2000; Widrow, Rumelhart, & Lehr, 1994) showed that Neural network classification can be successfully applied to a variety of real world classification tasks in industry, business and science.

Donald Specht developed the probabilistic neural network, in 1988 and 1990. The PNN can utilize to obtain a general solution for pattern classification problems. Bayesian classifiers is the approach in Donald Specht to estimate the likelihood of an input feature vector being part of a learned category, or class. To achieve the target which is minimizing the expected risk of wrongly classifying an object, this approach provides an optimum pattern classifier. This network consists of three layers; input layer, pattern layer, and output layer. The pattern layer organizes the training set, and output in literature sometime called the summation layer. Each input element is processed via pattern layer which relate to the same class and prepares that category for output (Anderson, D., & McNeill, G. 1992). This means that in pattern layer, for each input vector in training set a unique processing element is assigned. It can state that this process is very competitive. This means that the match to an input vectors is the highest match that program can develop. If this match is poor which means there is no relation between the input and patterns, no output is generated (Anderson & McNeill, 1992).

2.6.5 General Regression Neural Network

General regression neural network (GRNN) is a one-pass learning network algorithm, which accompanies PNN as alternatives to BPNN. GRNN is similar in form to the PNN (Specht D. F., 1991). Unlike the BPNN, these two networks do not depend on training parameters and are able to be applied directly in neural network architecture. (Beale M. &., 1998; Sinha, 2002). There are no training parameters such as learning rate and momentum as there are in BPNN, but there is a smoothing factor that is used when the network is applied to new data. The smoothing factor determines how closely the network matches its predictions to the data in the training patterns. (El-Sawah & Moselhi, 2014)

Using substantial simulations, Marquez and Hill (1993) showed that the GRNN sees through noise and distortion better than the BPNN. Whereas PNN finds decision boundaries between categories of patterns, GRNN estimates values for continuous dependent variables. Both do so through the use of nonparametric estimators of probability density functions (Specht D. F., 1991).

In summary, the GRNN is a three-layer network that provides estimates of its variables and converges to an underlying linear or nonlinear regression surface. The main advantages of GRNN are firstly, the ability of learning and training quickly with sparse data sets. Secondly, as the number of samples increases, the output converges to the optimal regression surface and lastly, the final estimate or output is always restricted by the minimum and the maximum of the observations (Petroutsatou, 2011; Specht D. F., 1991; Marquez & Hill, 1993).

2.7 SENSITIVITY ANALYSIS

While models incline to point out single outcomes, such as “the probability of power outage occurrence” the explanation of those results are expected to rely on the uncertainty of various factors involved to develop the model (Taylor, 2009). In dealing with these kinds of problems, a key question would be about the most important variables which has the greatest impact on the results. To assign rating of importance to each variables a “Sensitivity Analysis” model can be developed to examine the sensitivity of the model to changes in its inputs (Taylor, 2009) (Hunter, 2000). According to (Saltelli, 2008) sensitivity analysis is defined as the study of how uncertainty in the output of a model can be attributed to different sources of uncertainty in the model input.

The simplest form of sensitivity analysis is the “one way” model, in which the value of one element varies while the other factors are consistence to measure the effect of that variable upon the output error. This cycle is expected to be repeated for other factors to reach to a reasonable rating of importance to each of them. Consequently, a variable that is comparatively important will cause a huge damage in the model’s accomplishment. (Jain, 1997)

In such an analysis, it would be possible to generate a simple graph, plotting the main model outcome against each possible input value to demonstrate the relationship between the input value and the model’s results. (Taylor, 2009)

Similar to the problem statement of this research which is aiming to find the relation between weather situations and power outage, each weather factors (wind, temperature, precipitation, humidity, and lightning) might have different impact on the outcome. A sensitivity analysis can lead us to find the most affecting elements for further mathematical analysis.

2.8 SUMMERY OF EXISTING WORK

A reliable electricity supply is an essential resource for modern life. An interruption to supply has direct and indirect financial consequences that are generally many times greater than the value of the electricity not supplied, especially for large blackout events (Eurelectric, Power outages in 2003, 2004; Newman, 2011). As the reliability of electricity supply is important, so many researchers and scientific groups have done researchers about how and why blackouts are expected to happen. Do time, duration, location and size of the blackout have any effect on the damages and social cost of the incident? What are the risks threaten the bulk power systems? How can electrical companies get ready about risk of power outage in their territories? In the following paragraphs some previous works, which have been done earlier are explained.

As large blackouts are naturally caused by cascading failure distribution through a power system, (Baldick, et al., 2008) defines cascading failure for blackouts and provide a review of industrial tools, the challenges and emerging methods of analysis and simulation.

Hines in 2009 has published a study to determine what trends exist (or do not exist) in the available historical record of large blackouts in the United States between 1984 and 2006. His studies show that while technology has been grown during the time blackout frequency has not decreased. (Amin, 2008) and (Simonoff, 2007) both confirmed this idea and also suggested that the growth might be the result of increasing in number of reports about smaller blackouts. Furthermore, blackouts frequency changes seasonally and it changes in different hours of the day: Blackout frequency increases substantially during the late summer and mid-winter months; Blackout increases significantly during the peak hours. Hines (2009) claims that storm activity increases during mid-afternoon. (Carreras, 2004; Liao, 2004;

Dobson I. C., 2007) hold the idea that power networks being more stressed during mid-afternoon hours due to more public appeal.

(Carreras, 2004) and (Talukdar, 2003) studies show that the size of large blackout in the United States follow a power-law probability distribution. Carreras et al. (2004) argue that time-correlations in the blackout data give evidence of self-organized criticality, providing a plausible explanation for the power-law tail. (Dobson, Carreras, & Newman, 2005) describe a probabilistic model of loading-dependent cascading failure risk, which simulate a saturating electric power transmission system, and indicates that the number of failed components has a power-law region at a critical loading and a significant probability of total failure at higher loadings.

Since weather conditions are the most significant reasons of power outages, it has been so many researches investigating the impact of weather circumstances on the reliability of electric network. (Davidson, 2003) explores five hurricane disruptions in major Carolina electric power companies in terms of number of outages and customers affected; geographic distribution, duration, and causes of outages; and types of equipment affected to help develop a predictive model of disruption. Using outage, maximum gust wind speed, rainfall, and land cover data for analysis in his studies indicates that most damage is caused by trees. Also, maximum gust wind speed is a necessary but not sufficient predictor of disruption. Results provide a database to be used to help develop a vulnerability model that would support future hurricane emergency response and restoration activities.

(Winkler, 2010) during his investigation about the effect of hurricane damages upon power system reliability in Harris County, TX, USA, developed a model to predict failure probability for individual transmission and distribution power network elements simultaneously. Monte Carlo simulation (MCS) method is used to model the electrical reliability model, and to do that the most significant network damage predictors found by (Han, 2009) in their statistical analysis of outages, local terrain and wind speed, are utilized. The developed power system performance model generates rapid assessments of distribution and transmission level network damage through the use of component fragility models.

(Zhou, 2006) has developed two models to find the weather's impact in on overhead distribution lines' failure. This is expectant to help utilities make more efficient decision to gain the best operation and maintenance plan to decrease impacts of weather on reliabilities.

The models considered many groupings of the wind gust speeds and the lightning stroke currents into 15 weather states and attempted to find the probabilistic relationship between weather state and the failure level.

Since lightning is an important cause of outages in many electric power systems and poor system reliability, (Balijepalli, 2005) has developed a Monte Carlo simulation for assessing distribution system reliability under lightning storm circumstances. The author used the bootstrap method to model the lightning storm parameters. Also, an estimation of the temporary and permanent fault rate is gained from an analysis of the utility data to be used in the Monte Carlo simulation. Table 2-4. Summary of Previous Researches that Focused on Weather Impacts provides a summary about the previous researches that had focused on weather situations.

Table 2-4. Summary of Previous Researches that Focused on Weather Impacts

Title	Author	Summary and Limitations
Electric power distribution system performance in Carolina hurricanes	Davidson, R. A. - 2003	• Only few aspects of weather condition are considered (Rainfall and wind speed) • Only five big blackouts has been investigated

		• Model developed for a local region in the US
Performance assessment of topologically diverse power systems subjected to hurricane events	Winkler, J.- 2010	• Only few aspects of weather condition involving in hurricane are considered • Model developed for a local region in the US
Estimating the spatial distribution of power outages during hurricanes in the Gulf coast region	Han, S. R. - 2009	• Only effect of wind speed is investigated on the electrical reliability model
Modeling weather-related failures of overhead distribution lines	Zhou, Y - 2006	• Effect of wind speed and lightning is investigated for the probability of power outage
Distribution system reliability assessment due to lightning storms	Balijepalli, N. - 2005	• Checking the relation of lightning storm and probability of power outage

Also, some other studies focus on some other non-weather reasons that are able to cause power outages. For example, (Simonoff, 2007) studied the blackout data available from NERC for 1990 to 2004 with the approach of terrorist attack impacts. None of these disruptions during this period are a result of terrorist activity, but the authors claim that since there are similarity in the disruption in energy sector caused by power outage incidents, understanding the effects of "typical" disruptions would make it possible to estimate the effects of a terrorist-based disruption.

(Ren & Dobson, 2008) study 9 year time series of cascading transmission line outages of 200 line power system. They estimate the average propagation of the outages, through a risk model, which consider cascades and stages according to the outage times.

This research, data set for 1992 to 2009 are gathered and filtered in several ways to collect disturbances related to natural disasters and removed artifacts that could lead to misleading conclusions.

This work considers the disturbances in bulk power system related to natural disasters and weather conditions and provide a tool, which not only cover the previous works done by others, but also develop an artificial neural network model (ANN) which is able to provide more accurate results in predicting the probability of power outage based on weather forecasting. In This research, data set for 1992 to 2009 of system disturbances in North America are gathered and filtered in several ways to collect disturbances related to natural disasters and removed artifacts that could lead to misleading conclusions to provide an accurate tool which will be able to make recommendations for future companies performance in the same situation with electrical networks.

2.9 LIMITATION OF PREVIOUS LITERATURE

This chapter covered a wide continuum of topics to present an overview of the existing approaches to the power outage and blackout in bulk power system. Damage to electric power distribution systems can cause significant economic loss, business interruption, inconvenience, and permanent loss of data, food, and perishable goods. Furthermore, communication, water distribution, traffic signaling, and other lifeline systems that depend on electric power can be affected as well. Since electrical power supply has a significant role in today's life, maintenance of the bulk power system has been always a big concern of the power companies. Among all the different kind of risks, which threaten the power supply system, weather condition, natural disasters, hurricane and storms have the most number of causes of blackouts, which made scholars to do lots of research about this issue.

All the mentioned past works have developed models to find the impact of weather conditions on the reliability of power systems. The developed models do not consider all the weather factors (temperature, wind speed, precipitation, humidity and lightning) in one model. The developed model in this research covers all the weather factors, which make it individual for different seasons. Past works do not consider the consumption index of electricity in different months, which is related to both seasons and weather conditions and national events during the time. For example, consumption index in January is high, which is caused by cold weather and New Year Event lightning. This work focuses on four eastern Canadian provinces, i.e. Quebec, Ontario, New Brunswick and Nova Scotia. In the model developed in this work, network size is also a considered parameter to find its relation with number of power outage incidents. Some of the past works divide power outage of various part of the electrical power grid, while in this research, the concept of power outage had a more important role in the developed model. Moreover, previous works had mostly focused on the big blackouts that happened in a short period of time. This research focuses on both big blackouts and small power outages in an eighteen years period of time. Some of the past models that used historical data of power outages, same as current research, but different approaches like Monte Carlo simulation (MCS) were used to develop their models. In this research three types of ANN is used to recognize a pattern among weather circumstances and power outage incidents. Since ANN is a self-training model, is able to find patterns among the datasets, where there are complex relationships between the inputs and outputs.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 CHAPTER OVERVIEW

This research begins with a literature review (chapter 2) on electrical power grids, the risks that can threaten their reliability, how blackouts can affect society and finally focuses on weather conditions that can cause unreliability in power grids and on which tools can be used to predict these situations. Following the literature review, the research methodology identifies the prediction tools that can function well based on a wide variety of data. Three types of artificial neural network models are developed in this section: BPNN, GRNN, and PNN. The research methodology is followed by the data collection, which outlines the process used to collect the data for the identified factors that can trigger a power failure directly or indirectly. In order to verify and validate the system, a case study is conducted and will be continued with other case studies which consider more details in their model development. Finally, this research is finalized with some conclusions and recommendations as well as some proposed research areas for the future.

The generic flow diagram of this chapter is presented in **Error! Reference source not found.**. This chapter describes three models developed for predicting power outage likelihood of occurrences; i.e. BPNN, GRNN, and PNN and their validation process. It is followed by description of sensitivity analysis and estimation of social cost of electric power outage.

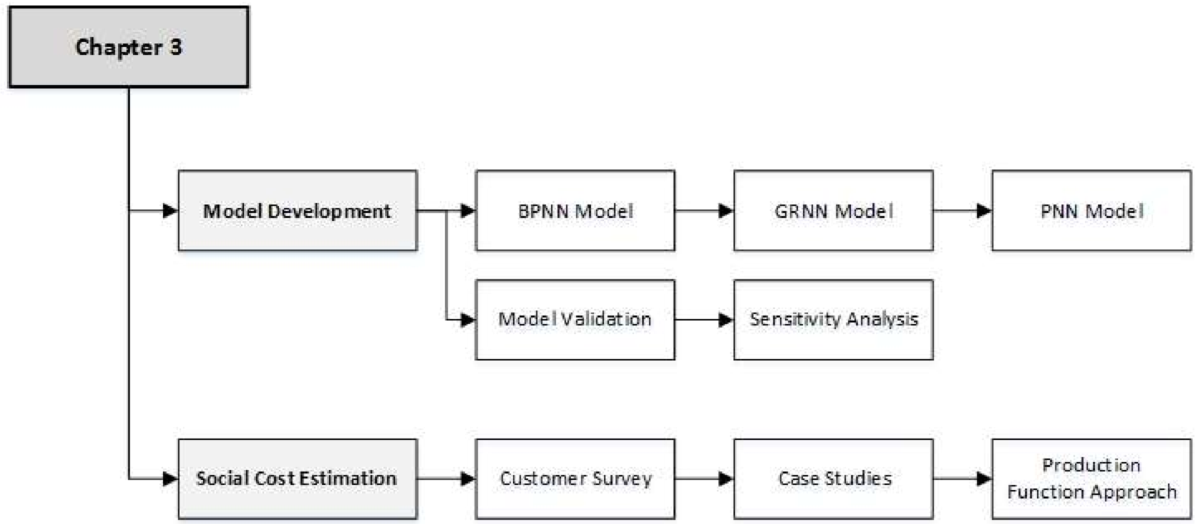

Figure 3-1. Chapter 3 Overview

3.2 LITERATURE REVIEW

The literature review was presented in Chapter 2. It comprehensively covered the major research areas related to risk asset management of power grids. As shown in Figure 3-1, the literature review consists of six sub-sections:

1) Electrical Power Grids
2) Social Costs of Power Outages
3) Risks in Electrical Power Grids
4) Risk Management
5) Artificial Neural Network
6) Sensitivity Analysis

The concepts, methods and applications of different approaches in each subject were elaborately discussed and the merits and shortcomings of each method compared to its counterparts were presented.

3.3 MODEL DEVELOPMENT

The purpose of this research is to find the relation between weather conditions and power outages. There are different approaches to solve the proposed problem, such as Fuzzy models, Regression models and ANNs. Fuzzy models do not have the ability of self-training and pattern recognition. Therefore, an expert person is needed to find the relationship(s) between the inputs and outputs. Regression models mostly give good results for linear relationships, and for more complex patterns higher degrees of regression are required. However, finding the best degree of regression in non-linear problems is completely a new study of optimization. Meanwhile, ANN models are known for their ability to self-train and recognize patterns between the inputs and outputs. This research aims to develop several ANN models to determine the most accurate approach in predicting the probability of power outages based on weather forecasting data.

This section provides a detailed explanation of the model development process. The flowchart of the techniques and actions that are required to implement the proposed framework is illustrated in Figure 3-2. This framework contains five main phases: 1) implementation of the BPNN model with dataset I, 2) performing sensitivity analysis to find the most important variable, 3) implementation of BPNN model with dataset II (dataset II collected based on the sensitivity analysis results), 4) implementation of GRNN model with dataset I & II, 5) implementation of PNN with dataset I & II, and 6) estimating the social cost of power outage in four sectors; i.e. residential, commercial, industrial and agriculture.

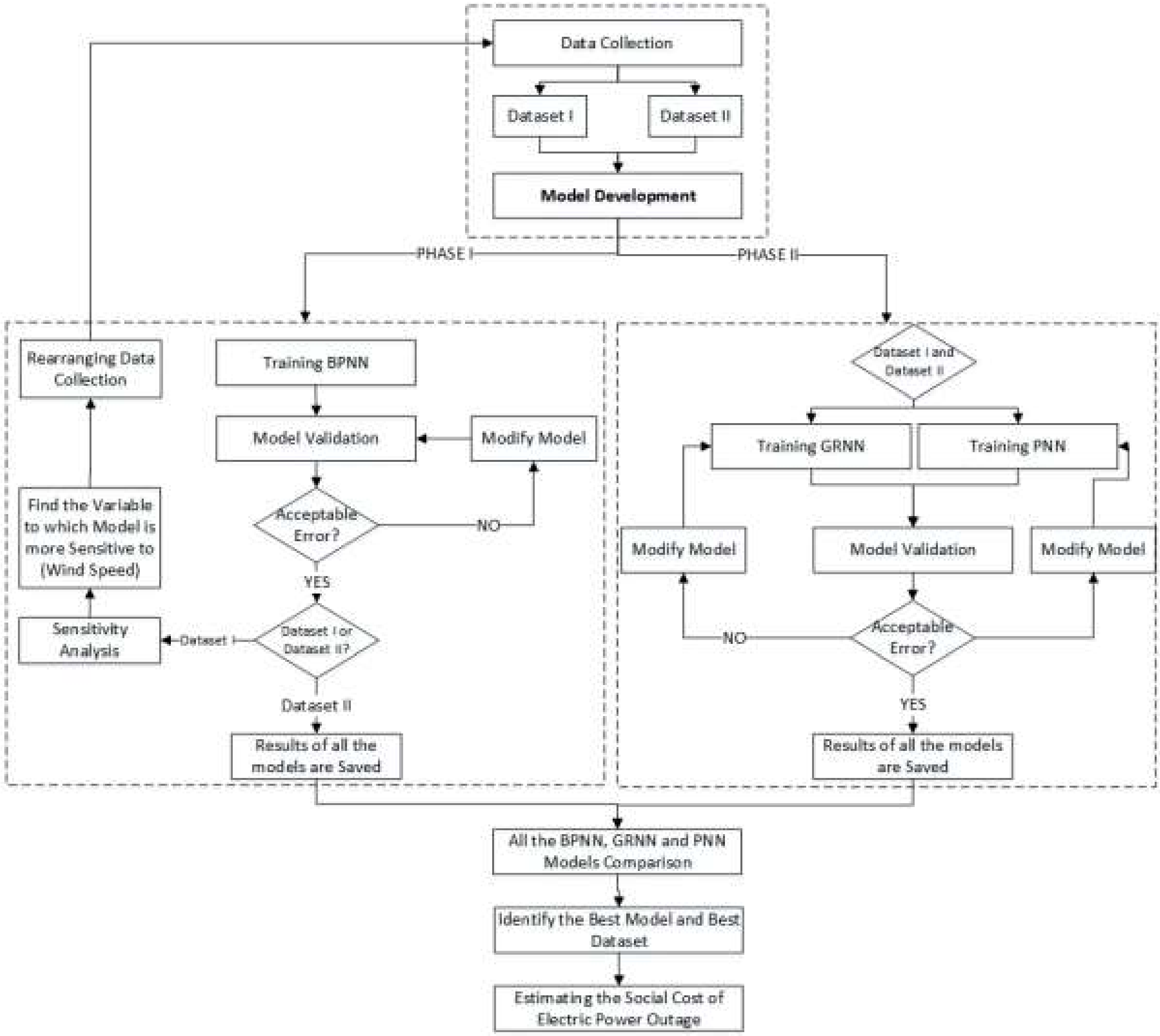

Figure 3-2. Framework of Research

3.3.1 Factor Identification

To start, variables that are correlated to the relationship of weather conditions and power outage are reviewed in the literature. These data are divided into three sections: 1) variables related to weather condition forecasting, 2) electricity consumption rates, and 3) electricity network size. Table 3-1 summarizes these variables.

Table 3-1. Variables Considered for Model Development

	Variables	Description	Source
Weather Variables	Wind Speed (km/hr.)	The maximum speed of motion of air in kilometers per hour (km/h) usually observed at 10 meters above the ground in 24hrs.	Canadian Climate Data - Environment Canada (http://climate.weather.gc.ca/advanceSearch/searchHistoricData_e.html)
	Temperature (C°)	The maximum temperature of the air in degrees Celsius (C°) in 24 hrs.	
	Precipitation (mm/s)	The sum of the total rainfall and the water equivalent of the total snowfall in millimeters (mm), observed at the location during a specified time interval.	
	Relative Humidity (%)	The maximum value for ratio of the quantity of water vapor the air contains compared to the maximum amount it can hold at that particular temperature.	
	Lightning	A sudden electrostatic discharge during an electrical storm between electrically charged regions of a cloud. This research considers lightning as if I had happened or not.	
Energy Consumption Index		Energy delivered and consumed at the facility level. Used as a monthly Index.	Electric Power Statistics-Statistics Canada (http://www.statcan.gc.ca/daily-quotidien/140822/dq140822c-eng.htm)
Power Network Size (km)		Size of the area that the electrical power grid supports for delivering power.	Hydro Companies Information

Weather variables include the temperature, wind speed, precipitation, relative humidity and lightning, collected via the "Canadian Climate Data - Environment Canada" database. These data are collected daily, meaning that while the extreme value of weather factors are gathered in one day; they are not necessarily happening at the same time during that day. The Electricity Consumption rate shows the actual energy demand at different years and months, which varies in different seasons according to weather conditions. This information is collected from "Electric Power Statistics- Statistics Canada". According to historical power outage reports, the number of power outage incidents might have a relation to the size of the power grid, which is therefore considered in this research to develop a more accurate model.

The network sizes are obtained from information provided by electrical companies. Further information is provided in Chapter 4: Data Collecting. All of the above information is collected for four eastern provinces of Canada: Quebec, Ontario, New Brunswick, and Nova Scotia.

3.3.2 Data Preparation

This section gives some brief information about how the data collection was carried out for this research. The following chapter (Chapter 4: Data Collection) provides more details about data collection. Information about the time, location, size, cause of blackout incidents, and number of affected customers for the period 1992 to 2009 was collected from "system disturbances reports" provided by the North American Electric Reliability Council (NERC). These reports are the results of the Disturbance Analysis Working Group's (DAWG) investigations, which review and analyze the disturbances that occur on the bulk electric systems of North America to determine the reasons for those disturbances, to ensure that the improvements to avoid recurrence are appropriate, and to share the lessons learned with the industry (North American Electric Reliability Corporation, ERO Data Analysis System, 2013; Kröger, 2011).

The NERC works with eight regional entities, which together account for all the electricity delivered in the United States, Canada, and a portion of Baja California Norte, Mexico (North American Electric Reliability Corporation, Regional Entities, 2013). The Northeast Power Coordinating Council (NPCC) zone consists of the State of New York and the New England states as well as the Canadian provinces of Ontario, Quebec, New Brunswick and

Nova Scotia. This research focuses on the eastern Canadian region of the NPCC. The following paragraphs introduce the data collection approaches.

3.3.2.1 Weather Conditions Variables

Based on the disturbances system reports, the blackout days caused by weather conditions are identified for the period 1992 to 2009. To find the difference between the weather conditions of a day that power outage occurred and the regular weather conditions of the same day, weather variable values are collected for the years between 1992 and 2009 for that day; i.e., for each power outage day, the weather conditions for the same day were collected over seventeen years. These datasets were gathered through the "Canadian Climate Data - Environment Canada" service in two sections. In dataset I the extreme values for each factor in a day were collected, i.e. the extreme values for every factor that might not happen in the same hour of that day. New datasets are collected in dataset II, after developing a sensitivity analysis and finding the factor that the model is most sensitive to, containing the extreme value for the most critical factor and the value of other variables at the same timing when the critical factor reached its extreme value.

3.3.2.2 Energy Consumption Index

Energy consumption is another important factor that influences blackout incidents. Energy consumption varies with weather conditions (cold or warm seasons), geographical location (varying lengths of daylight hours), and national events (New Year in winter and entertainment festivals in summer), etc. To develop a more accurate model, an energy consumption index was added to the other inputs for model training. These data are collected from “Electric power statistics – Environment Canada”, which shows a consumption index that follows a sinusoidal path over different years; averages of these numbers are provided in Table 4-4 (Statistics Canada, 2014).

3.3.2.3 Electrical Network Size

As the size of the power grid increases, its maintenance gets more complicated. As it covers a bigger and bigger area, the probability of a power outage happening is expected to grow (Kaplan, 2009). System disturbance reports show that the number of power outages varies across provinces (Figure 4-10). As illustrated in Figure 4-10, the number of blackout incidents in Quebec is much higher than in other provinces. On the other hand, Quebec generates the biggest amount of electricity in all of Canada. The Quebec power network’s size is about 305,600 km, while for Ontario, New Brunswick and Nova Scotia it is 152,000 km, 31,550 km, and 31,800km, respectively.

3.3.3 BPNN Model

In the next step, an ANN was developed to find a relation between the input and output data sets. ANN is a mathematical model which finds patterns among datasets where there are complex relationships between the inputs and outputs. It stores those patterns and then uses them to analyze and apply problem solutions (Anderson & McNeill, 1992). Zayed and Halpin (2005) mentioned that ANN are composed of two phases namely: learning or training, and recalling. Finding the relationship(s) between the variables throughout the neural network is accomplished during the learning phase, which is monitored based on the errors of the produced network. The second function is called recalling, the inputs to the trained network are inserted, creating predictive responses. If in the training phas the output is available in the entry data, it is called supervised; otherwise it is known as unsupervised. Neural networks makes several learning techniques available; the most popular one is the back-propagation approach, which is able to offer a useful role in this research. This BPNN technique provides a suitable platform for risk management research since dealing weather forecasting data entails much uncertainty. Both the design of the network architecture and the learning elements' definitions, including the transfer function, the learning rate, and the number of epochs are very important elements. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer; the number of hidden layers may increase according to the complexity of the problem. The neurons of each layer are connected to the neurons of the next layer through the connection lines, each of which has a weight that is multiplied by the inputs transferred from the previous layers. To start the process, some random values are assigned to the weights and biases. Once the process runs, the accuracy errors are measured and the weights and biases are changed appropriately. The network checks the pattern at the stopping points called epochs, where the training is stopped at the point where a predefined termination condition is reached. After developing this process, the trained method can be used for any upcoming set of data in which there is a similarity or connection between the inputs and the output data (Bryson, 1975; Werbos, 1974; Alpaydin, 2014; Rumelhart, 1998; Moselhi, 1991). Figure 3-3 shows the BPNN model structure.

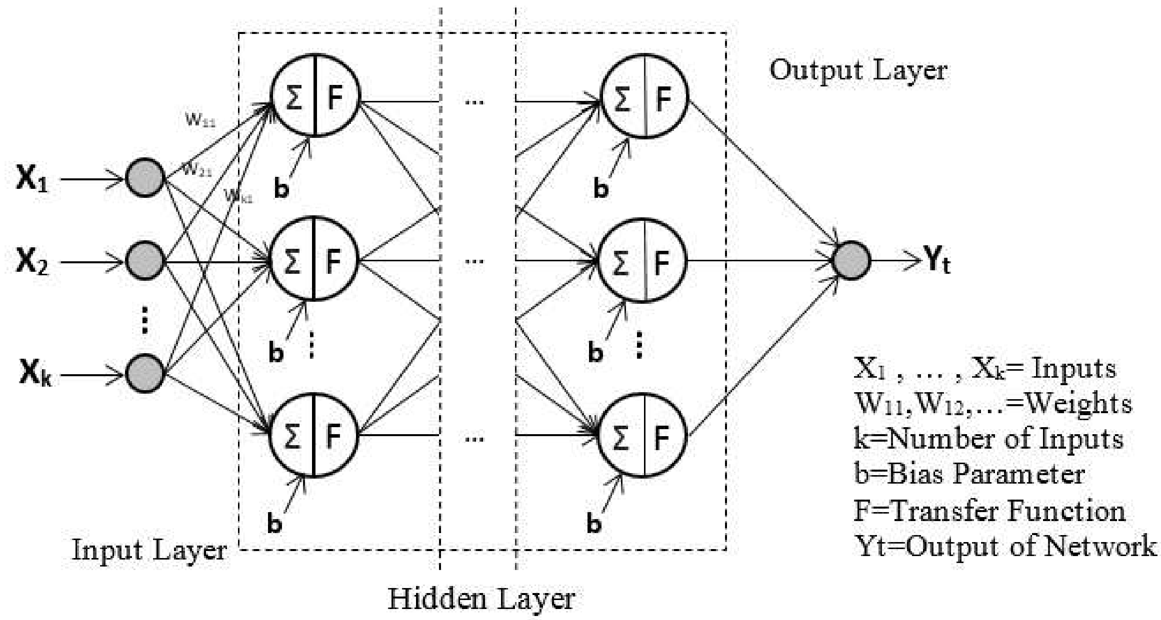

Figure 3-3. Schematic Diagram of a Multi-Layer Feed Forward (Zhu, Lee, Hargrove, & Chen, 2007)

The first step is to categorize the datasets, which means that the datasets are randomly divided into two parts, for training data and for test data. Training data is 85% and testing data is 15% of the complete datasets. The training data is divided into three categories: 1) 70% for training the model, 2) 15% for testing the model, and 3) 15% for validating the model.

A test set is used to evaluate how well the model copes with data outside the training set, and a validation set is used to evaluate the model adjusted in the testing step (Kareem, 2014). The dataset distribution is indicated in Figure 3-4. To determine the number of hidden layers, Khaw (1995) suggested having (2n+1) neurons in the first hidden layer and (2n+1)/3 in the second one, where *n* is the number of input factors. Based on this formula, there are 15 neurons in the hidden layer.

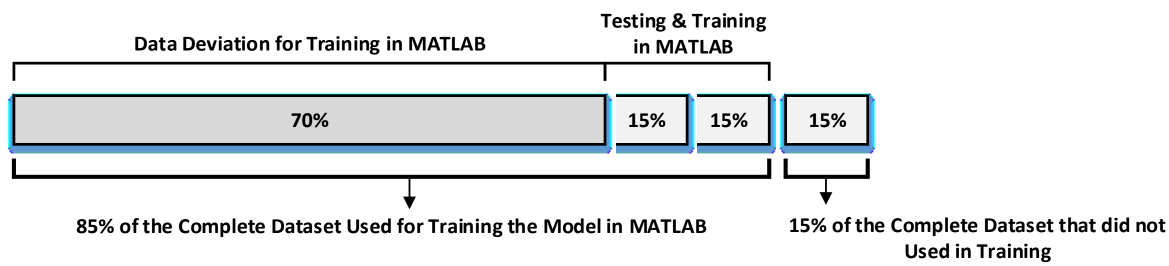

Figure 3-4. Distribution of Dataset

The common problem that occurred during the ANN training was what is called over-fitting. This is when the calculated estimation error for the training sample is very small, but the error for a new set of testing data is quite large. It could be stated that the network has memorized the training data points and it is thus not able to generalize the prediction for new cases. One way to improve the quality of the generalization in a trained net is known as regularization. Regularization involves applying another performance measurement other than the sum of the squared output errors, which is usually selected as the performance indicator. The Bayesian Regularization algorithm, as a regularization method, combines squared errors and weights in a mathematical relationship and minimizes them in order to find the combination that has the best generalization ability. Bayesian regularization of the weights and biases of the network are assumed to be random variables that get updated according to the Levenberg-Marquardt optimization. Bayesian Regularization allows the network have smaller weights and biases, which will, in turn, result in less susceptibility to over-fitting (MacKay 1992; Beale, Hagan, & Demuth, 2015).

A more detailed explanation of the Bayesian Regularization algorithm is out of the scope of this research. All of the assembled ANNs in this model are trained based on this learning algorithm, which can greatly improve the model's performance for future applications. The command `net.trainFcn = 'trainbr'` changes the default learning function of the program to Bayesian Regularization.

3.3.4 Model Validation

To determine how accurate the developed model is and also to find its error mathematical validation is used. Three different approaches are used to check the model mathematically, namely, root mean square error (RMSE), mean absolute error (MAE), and regression squared (R^2). The RMSE represents the difference between the values predicted by a model and the actual values. RMSE is a good measure of accuracy, but only to compare the forecasting errors of different models for a particular variable and not between variables. Eq. (3-1) indicates the formula for this index (Hyndman, 2006).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad \text{Eq. (3-1)}$$

In Eq. (3-1), y_i represents the values of actual outputs, $\hat{y}_i$ indicates the values of the predicted outputs released by the developed model, and n shows the number of outputs.

The MAE is a quantity used to measure how close forecasts or predictions are to the eventual outcomes; in other words, MAE measures the average value of the errors in a set of forecasts and checks the accuracy of the variables. The formula is shown in Eq. (3-2), in which, as in the previous equation, y_i represents the values of the actual outputs; $\hat{y}_i$ indicates the values of the predicted outputs released by the developed model, and n shows the number of outputs (Hyndman, 2006).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad \text{Eq. (3-2)}$$

The MAE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be larger than or equal to the MAE; the greater the difference between them, the greater the variance in the individual errors in the sample. If the RMSE=MAE, then all the errors are of the same magnitude (Chai & Draxler, 2014).

In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1 indicates that the regression line perfectly fits the data (Glantz, 1990). The R^2 formula is given as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2} \qquad \text{Eq. (3-3)}$$

Where $\bar{y}_i$ indicates the average value of actual outputs. The other parameter definitions in Eq. (3-3) are the same as in the two previous formulas.

3.3.5 Sensitivity Analysis

Once the BPNN model has been trained, the sensitivity of the model to changes in its inputs variables, or a "Sensitivity Analysis" can be useful (Taylor, 2009). Inother words, the sensitivity analysis defines how the uncertainty in the input variables, temperature, wind speed, precipitation, relative humidity, lightning, electricity consumption index and electricity network size can change the failure type of the model.

In sensitivity analysis, one model parameter is changed at a time while the remaining model parameters are fixed to a nominal value. To start, the differences between the minimum and maximum values of all the variables are calculated. Afterward, the ratio number is added to the minimum value of each variable in ten steps to reach the maximum value of that variable. Other factors are the average value of each variable. This cycle is repeated for other factors and the results are compared to identify the variable that is comparatively important and can cause a huge damage to the model's accomplishment (Jain, 1997). In such an analysis, it would be possible to generate a simple graph, plotting the main model outcome against each possible input value to demonstrate the relationship between the input value and the model's results. (Taylor, 2009). Since the range of the values of various factors are different, and also to have one graph showing the effect of various factors on the model, the outputs can be normalized. Eq. (3-4) can be used for this purpose, where $x = (x_1, \dots, x_n)$ and z_i is the i^{th} normalized data.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \qquad \text{Eq. (3-4)}$$

By normalizing the outputs, one simple graph can be generated to indicate the sensitivity analysis, showing the effects of changing all of the factors on the model's results.

3.3.6 Model Comparison (BPNN, GRNN and PNN)

The sensitivity analysis in the previous stage identified the factor that the model is most sensitive to its changes. To increase the accuracy of the developed model, a new sets of data is collected to consider the real effect of this most critical factor. New sets of data include the extreme value of the critical factor, while the other factors are collected at the same time of the day when the extreme case of the critical factor occurred. Since the first sets of data encompass the extreme case of the entire factor over a day (no matter what time it happened), new sets of data can indicate a ratio of the importance of the most critical factor and decrease the model's errors.

Two other approaches are used to increase the precision of the final results of this research to find the probability of power outages based on the weather conditions. Two other types of

ANN models are developed to find the most precise model: PNN and GRNN. The general architecture of these two models are the same as that of the BPNN, i.e. dataset distribution for training and testing. The number of hidden layers are also similar.

3.3.6.1 GRNN Model

A GRNN is a three-layer network with one hidden layer. The hidden layer, which sometimes refers to the regression network, consists of two slabs: pattern units and summation units. GRNNs are known for their ability to train quickly on sparse data sets (Specht D. F., 1991). Figure 3-5 shows a GRNN Block Diagram.

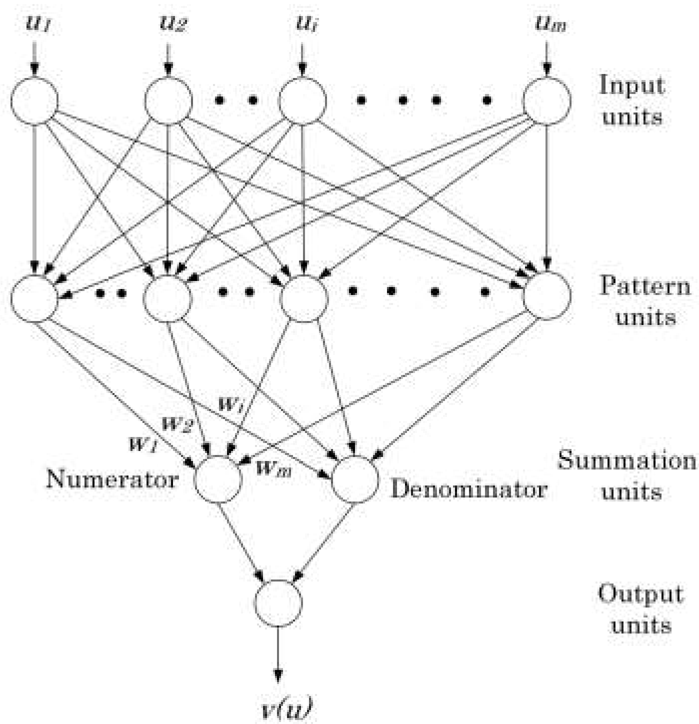

Figure 3-5. GRNN Block Diagram (Halder, Tahtali, & Anavatti, 2014)

The architecture form of GRNN is similar to PNN. Whereas a PNN finds decision boundaries between categories of patterns, a GRNN estimates the values for continuous dependent variables. GRNN responds much better to many types of problems than a BPNN.

There are no training parameters such as learning rate and momentum as in BPNN, but there is a smoothing factor that is used when the network is applied to new data. The smoothing factor determines how closely the network matches its predictions to the data in the training patterns. A higher smoothing factor causes a more relaxed surface that fits through the data. I It is recommended to allow the network to choose a smoothing factor and then to try to find a better one through iterations or any other optimization procedure (Kiefa, 1998; El-Sawah & Moselhi, 2014).

GRNNs can have multidimensional inputs, and they will fit multidimensional surfaces through data. Unlike BPNNs, which propagate training patterns through the network multiple times seeking a lower mean square error between the network's output and the actual output or answer, GRNN's training patterns are only propagated once through the network.

GRNNs work by measuring how far a given sample pattern is from patterns in the training set in N-dimensional space, where N is the number of inputs to the problem. A GRNN is more advantageous with sparse and noisy data than a BPNN, and it takes much less time to train. (Kiefa, 1998; Specht D. F., 1991; Marquez & Hill, 1993).

3.3.6.2 PNN Model

One disadvantage of a BPNN is that it can take a large number of iterations to converge to the desired solution. An alternative to BPNN that has been used in classification is the PNN, which involves one-pass learning and can be implemented directly in neural network architecture (Specht D. F., 1990).

PNN can be used for mapping, classification, associative memory, or to directly estimate a posteriori probabilities. PNN can be utilized to obtain a general solution for pattern classification problems. Figure 3-6 indicates the typical scheme of a probabilistic neural network.

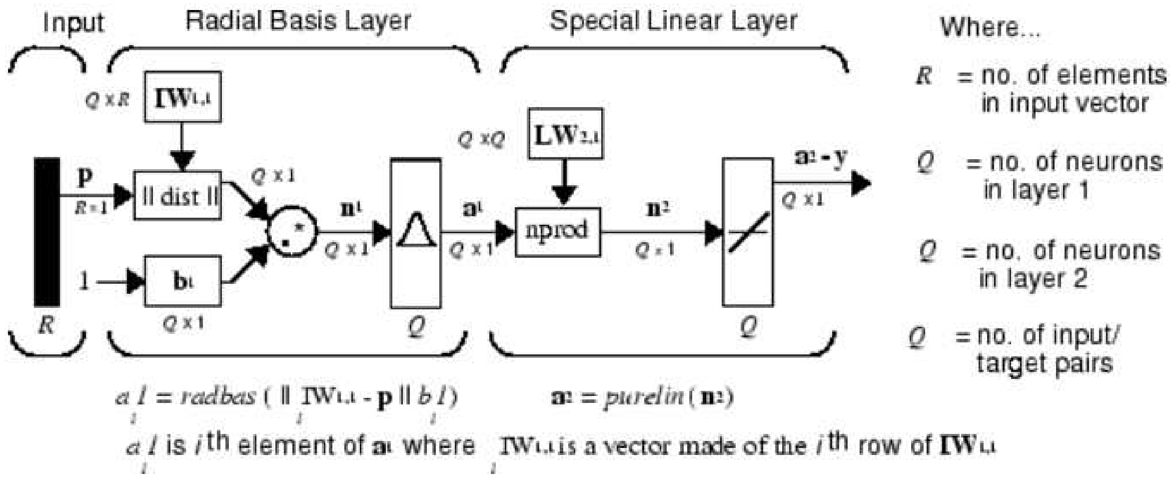

Figure 3-6. A Probabilistic Neural Network Example

Each input element is processed via a pattern layer which relates to the same class and prepares that category for output (Anderson & McNeill, 1992). The first-layer input weights, $IW^{1,1}$ are set to the transpose of the matrix formed from the Q training pairs. When an input is presented, the || *dist* || box produces a vector whose elements indicate how close the input is to the vectors of the training set. These elements are multiplied by the bias, element by element, and sent to the transfer function. The second-layer weights, $LW^{1,2}$ are set to the target vectors' matrix. Each vector has a 1 in the row associated with that particular class of input, and 0s elsewhere. Thus, the network classifies the input vector into a specific class because that class has the maximum probability of being correct (Mathworks, 2015).

Operationally, the most important advantage of PNNs is that their training is easy and instantaneous; it can be used in real-time because as soon as one pattern representing each category has been observed, the network can begin to generalize to new patterns. The other advantage of PNNs is that the shape of the decision surfaces can be made as complex as necessary, or as simple as desired, by choosing the appropriate value for the smoothing parameter (Kiefa, 1998).

3.4 SOCIAL COST ESTIMATION METHODS

There are different approaches to quantifying electricity interruption costs. The three most common methods are: case studies, the production function approach and customer surveys.

3.4.1 Case studies

Past events, such as the blackouts in California in 2001 and 2002, can be used to quantify the cost of power interruptions. The advantage of this method is that these estimations are based on real events rather than hypothetical scenarios. It is easier for electricity consumers to provide detailed cost evaluations when they have experienced an interruption. However, this methodology is limited by the specific characteristics of the outage studied (e.g., place, time, duration); and it is difficult to generalize the results (Linares & Rey, 2012).

3.4.2 The Production Function Approach

This method uses the ratio of an economic measure (e.g., gross domestic product, gross value added) and a measure of electricity consumption (e.g., kWh) to estimate interruption costs by sector. The objective is to find the value of one unit of electricity, also known as the Value of lost load (VoLL). Under the production function approach, it is assumed that electricity is essential for production, which is not always true. In some sectors, an electricity interruption does not necessarily imply a production break. Therefore, this method may overestimate electricity interruption costs (Linares & Rey, 2012).

3.4.3 Customer Surveys

In this method, surveys are employed to obtain information from industrial, commercial and residential sector customers. The objective is to obtain a direct or indirect valuation of interruption costs from customers themselves. Direct approaches are employed for those customers with a good knowledge of their interruption consequences (e.g., in the industrial sector and other large electrical users), while indirect evaluation methods are employed when interruption impacts are less tangible and the monetary loss is more difficult to evaluate (e.g., for the residential sector).

Customers are asked to identify the impacts and evaluate the costs related to an electricity interruption. Usually people are asked about their willingness to pay (WTP) to avoid interruptions, or their willingness to accept (WTA) a compensation for having a higher number of interruptions. Consumers will tend to overestimate their interruption costs to free-ride on the system. On the other hand, they can also be motivated to underestimating them if their contribution to paying for the cost of security of supply is higher than their share of the costs of an interruption (Linares & Rey, 2012)

3.4.4 Comparison and Discussion

The three methods have their advantages and disadvantages. Hence, when analyzing the costs of electricity interruptions, it is important to consider the cause and characteristics of the interruption. The survey method approach can be appropriate to estimate the costs in electricity shortages as a result of a drought, nuclear crisis, etc., and also for sectors for which the supply of electricity is critical. Customer surveys are more accurate at estimating social and indirect economic impacts, and therefore, this method should be employed when analyzing interruption costs related to poor power quality and mechanical failures due to weather conditions. In some sectors, such as industrial users, indirect and social impacts are very important, and thus surveys can be used to capture these costs. This survey method is in effect, the direct societal cost of unreliability. The survey method also can reflect the users' actual needs. Customer-specific costs are the losses that various customers experience due to the unavailability of the functions, products and activities that are dependent upon electricity. The best source of this information is the customers themselves. Variations of the customer survey approach appear to be growing as the method of choice for utility purposes (Wacker & Billinton, 1989; Wacker & Tollefson, 1994).

Wacker and Tellefson (1994) developed a survey study about customers' understanding of the impact of supply interruptions on their activities that depend upon electricity and the associated costs. The study was done for the Natural Sciences and Engineering Research Council (NSERC) in conjunction with eight Canadian electrical utilities. Four sectors (i.e., Residential, Agriculture, Industrial and Commercial) were utilized to calculate the social cost of loss of electricity. Wacker and Tellefson (1994) used an 'aggregated average' approach to normalize the data, which was defined as the ratio of the sum of the costs and the sum of the demand. In this present research, information from Wacker and Tellefson (1994) is used for estimating the cost of power outages in different categories. The social cost of power outages needs to be updated to reflect the current costs of electricity consumption and how it is charged.

3.5 SUMMERY

The choice and the design of the ANN model significantly affect the results obtained from the model, as well as the value of the variables in two sets of data. Three types of the ANN model are developed for two sets of data. In general, six ANN models are developed: BPNN, GRNN, and PNN models, each for two types of datasets, the details of which will be explained in Chapter 4: Data Collection. The structures of these three types of models were explained in this chapter, along with a comparison of their abilities to provide results. A model validation methods to find the best model that provides the optimal performance was then described.

Information achieved in previous studies was used to calculate the social cost of power outage incidents in the four categories of residential, agriculture, industrial and commercial users. Customer survey were used to identify the impacts and evaluate the costs related electricity interruptions. The electrical costs for each sector is then should be updated to the present electricity consumption price and electricity consumption rate.

CHAPTER 4: DATA COLLECTION

4.1 CHAPTER OVER VIEW

Data collection is the act of gathering information about certain variables in order to examine hypotheses, answer research questions, and evaluate results. This chapter aims at introducing the data collection process and the description of the processed data. Figure 4-1indicates the overview of this chapter. Section 4.2 and 4.3 reviews the literature related to NERC organization and their submitted system disturbances reports. These reports provide information about the time, location, size and cause of blackouts incidents in the North America. Section 4.4 explains about the available data sources; i.e. environment Canada, statistics Canada, electric companies, and customer surveys. Datasets can be collect throughout of these data sources. The identified effective factors on electric power outage are categorized into three type; i.e. 1) weather variables (i.e. wind speed, temperature, precipitation, humidity and lightning), 2) electric energy consumption index and 3) electric power network size. Summary of variables are describes in Table 4-1.

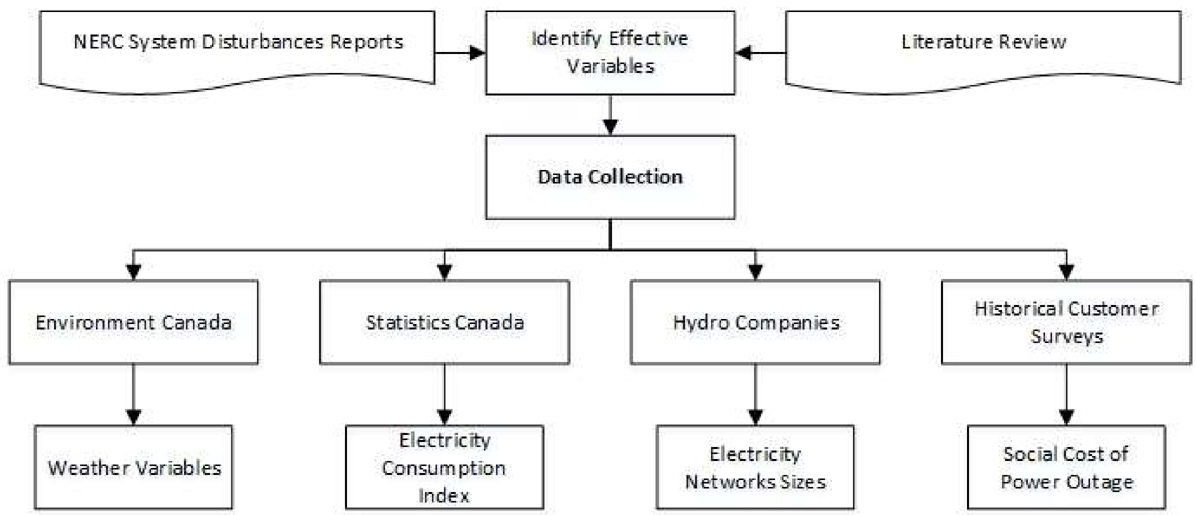

Figure 4-1. Chapter 4 Overview

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Table 4-1. Summary of Variables and their Description

Variables		Description
Weather Variables	**Wind Speed (km/hr.)**	The maximum speed of motion of air in kilometers per hour (km/h) usually observed at 10 meters above the ground in 24hrs.
	Temperature (C°)	The maximum temperature of the air in degrees Celsius (°C) in 24 hrs.
	Precipitation (mm/s)	The sum of the total rainfall and the water equivalent of the total snowfall in millimeters (mm), observed at the location during a specified time interval.
	Relative Humidity (%)	The maximum value for ratio of the quantity of water vapor the air contains compared to the maximum amount it can hold at that particular temperature.
	Lightning	A sudden electrostatic discharge during an electrical storm between electrically charged regions of a cloud. This research considers lightning as if I had happened or not.
Energy Consumption Index		Energy delivered and consumed at the facility level. Used as a monthly Index.
Power Network Size (km)		Size of the area that the electrical power grid supports for delivering power.

4.2 NORTH AMERICAN ELECTRIC RELIABILITY CORPORATION (NERC)

The North American Electric Reliability Council (NERC) is an international regulatory authority whose mission is to ensure the reliability of the bulk power system (BPS) in North America. Both the US Department of Energy (DOE) and the NERC oblige that member organizations submit reports when adequately huge disturbances happen within their domains such as electric service interruptions, unusual occurrences, demand and voltage reductions, public appeals, fuel supply problems, and acts of sabotage that can disturb the reliability of the bulk electric systems (Hines P. , 2008; North American Electric Reliability Council , 2004).

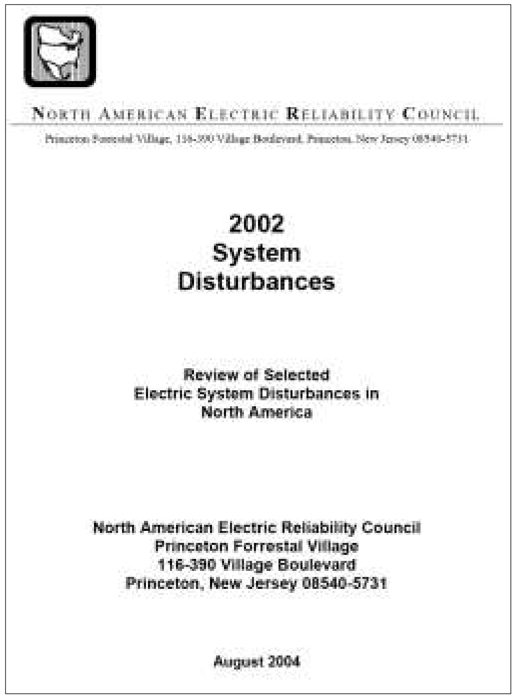
DOE only publishes reports while NERC provides a database through its Disturbance Analysis working Group (DAWG). The DAWG chooses those disturbances reports that are valuable to the industry, afterward requests the local council or utilities involved for a full report of each power outage occurrence (North American Electric Reliability Council , 2004). Law demands utilities and other load serving entities to submit reports of all disturbances that terminate more than 300 MW or 50,000 customers (U.S. Department of Energy, 2014). Some smaller disturbances are also included in the reports, but on a less predictable basis, while large blackouts can be recorded in several reports. For example, the August 14, 2003 event is recorded in six reports (Hines P. , 2008). The disturbances data (NERC data) are the results of the Disturbance Analysis Working Group (DAWG) investigating work. Since the NERC and DAWG database are the best-recorded source, providing data on blackouts, “system disturbances reports” from 1992 to 2009 is used in this research to find data about power outages during this period (North American Electric Reliability Corporation, 2013)

4.1.1 System Disturbances Reports

NERC bulk power system awareness gathers and examines information on system disturbances and other events that have an influence to the North American bulk power system.

(North American Electric Reliability Corporation, 2013). The main purpose of analyzing system disturbances events and preparing are to specify the reasons of those happenings, to assure the movements to avoid recurrence are correct, and to offer lessons learned to the industry. The event analysis also prepares useful inputs for training the models related to power outages occurrences and reliability standards development. Moreover, it classify starting events causes such as natural disasters, equipment failure, human error, demand–supply misbalance, intentional attacks, etc., all of which support continued reliability improvement of bulk power system. (North American Electric Reliability Corporation, 2013; Kröger, 2011).

In this research system disturbances reports from 1992 to 2009 have been studied to collect data about the causes that can trigger electric power outage. In every report, information about each power outage event is explained in details, covering size, time, location, and cause of that incident. Once the blackouts are giant or have significant side effects, several individual reports might be assigned analyzing the incident. Figure 4-2 and Table 1 indicate sample of system disturbances reports that are used for data collection about electric power outage.


NORTH AMERICAN ELECTRIC RELIABILITY COUNCIL

Princeton Forrestal Village, 116-390 Village Boulevard, Princeton, New Jersey 08540-5731

2002
System
Disturbances

Review of Selected
Electric System Disturbances in
North America

North American Electric Reliability Council
Princeton Forrestal Village
116-390 Village Boulevard
Princeton, New Jersey 08540-5731

August 2004

Figure 4-2. A Sample of System Disturbances Reports (North American Electric Reliability Council , 2004)

Table 4-2. Sample of Summarized Information of Power Outages in 2002 (North American Electric Reliability Council , 2004)

Date	Region	Utilities	Type*	MW	Customers	Cause
01/30-31/02	SPP	Oklahoma Gas & Electric, Kansas City Power & Light Co., and Missouri Public Service Co.	INT	1,210-1,310	570,000	Weather – ice storm
02/27/02	NPCC	Independent Electricity Market Operator	INT/VR	0	0	Equipment failure
02/27/02	WECC	San Diego Gas & Electric Co.	INT	340	210,882	Human error
02/28/02	WECC	California Independent System Operator	DR	0	N/A	Broken static wire
03/09/02	ECAR	Consumers Energy Company	INT	190	190,000	Weather – severe storm
03/09/02	NPCC	Independent Electricity Market Operator	INT	196	46,000	Weather – strong winds
03/20/02	**WECC**	**Power Pool of Alberta**	**INT**	**274**	**17,000**	**Equipment failure**
03/21/02	NPCC	Hydro-Québec – TransÉnergie	UO	0	0	Human error
03/25/02	NPCC	New Brunswick Power Corp.	UO	0	0	Logging activity
03/30/02	SERC	Georgia Power Company	UO	0	0	Weather – lightning & system protection misoperation
04/17/02	WECC	Arizona Public Service Co.	UO	0	0	Equipment failure
04/23/02	**ECAR**	**American Electric Power and Indianapolis Power & Light Company**	**INT**	**39**	**1**	**Equipment failure**
04/27/02	MAPP	Manitoba Hydro	UO	0	0	Equipment failure
04/29/02	**FRCC**	**Jacksonville Electric Authority**	**INT**	**2,100**	**360,000**	**Equipment failure**

To simplify and organize information, the NERC has divided the BPS of North America into eight zones, three of which consist of both US states and Canadian provinces, as it is indicated in Figure 4-3. These entities account for all the electricity delivered in the United States, Canada, and a portion of Baja California Norte, Mexico (North American Electric Reliability Corporation, Regional Entities, 2013):

- Florida Reliability Coordinating Council (FRCC);
- Midwest Reliability Organization (MRO);
- Northeast Power Coordinating Council (NPCC);
- Reliability First Corporation (RFC);
- SERC Reliability Corporation (SERC);
- Southwest Power Pool, RE (SPP);
- Texas Reliability Entity (TRE);
- Western Electricity Coordinating Council (WECC).

Figure 4-3. NERC Entity Regions (North American Electric Reliability Corporation, Regional Entities, 2013)

4.2.1 Northeast Power Coordinating Council (NPCC)

NPCC zone is in charge of supplementing the reliability of the bulk power system in North-eastern North America. Geographically, the NPCC district contains the State of New York and the six states of New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont) as well as the eastern Canadian provinces of Ontario, Quebec, New Brunswick and Nova Scotia (Figure 4-4). Generally, the territory covered by NPCC is about 1.2 million square miles, populated by more than 55 million people. NPCC covers approximately 45% U.S. and 55% Canadian for load perspective. Around 70% of Canadian net energy for load is within the NPCC Region (North American Electric Reliability Corporation, 2013)

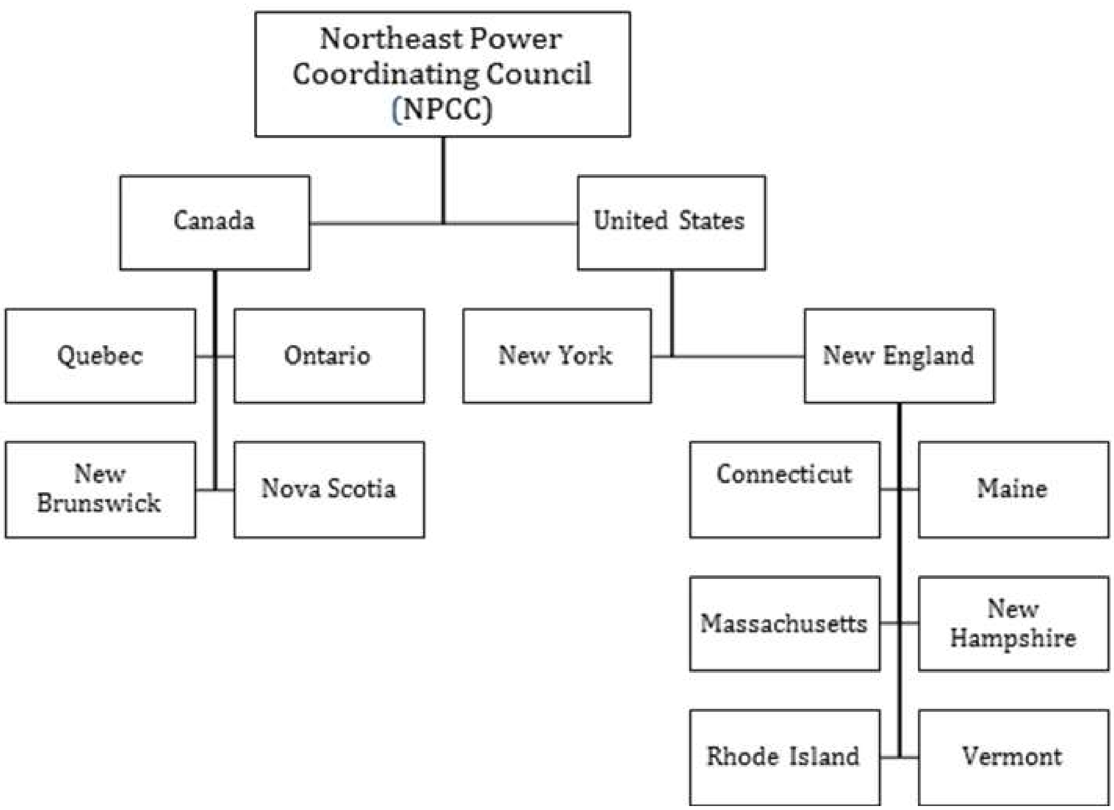


Figure 4-4 NPCC Territory

In this research, the blackout data are collected from NPCC zone, and focuses specifically on the Canadian part; i.e. Quebec, Ontario, New Brunswick and Nova Scotia. System disturbances reports from 1992 to 2009 shows that there were 189 numbers of electric power outage incidents happened in the NPCC territory during eighteen years. There were various reasons that triggered power outages, e.g. weather disaster, equipment failure, voltage reduction, human error, fire, maintenance error, public appeal, terrorist attack, hidden factors, etc. as the reports show, weather events have the most number of causes of electric power outages; i.e. 60 days (Figure 4-5). Reports also indicate that among the 60 days of power outage in NPCC zone, 38 days were happened in Canada. Since the weather condition is more critical, this research focuses on Canada territories; i.e. Quebec, Ontario, New Brunswick and Nova Scotia.

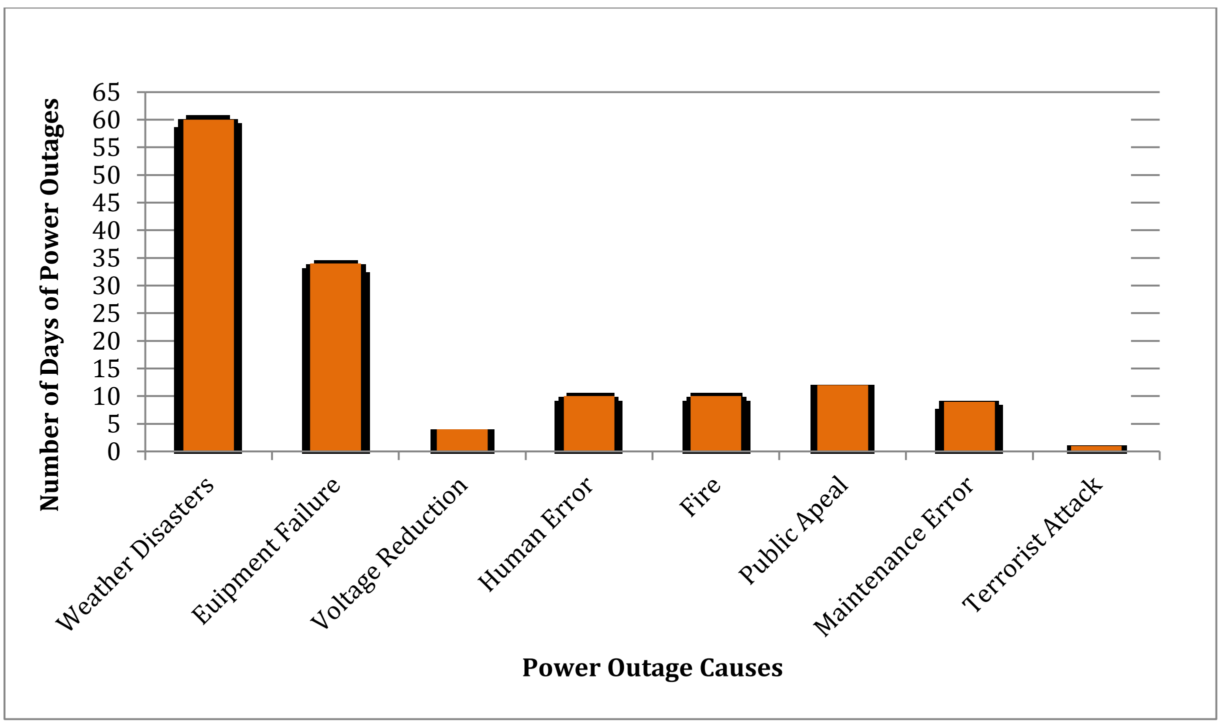


Figure 4-5. Comparison of Power Outage Causes during 1992 to 2009 in NPCC Zone

4.2 DATA COLLECTION

Following paragraphs prove explanation about data sources of each variable, and how they are collected for the purpose of this research.

4.2.1 Weather Variables

Since weather conditions triggered the most number of power outage incidents, this research focuses on the effects of weather factors on the likelihood of blackout occurrences. More detailed investigation in the system disturbances reports indicates the most effective weather variables on electric power grids (Figure 4-6). These variables are categorized into five main groups; i.e. wind speed, temperature, precipitation, humidity and lightning. Description of these provided in Table 4-1. Figure 4-7 also compare the number and causes of electric power outage incidents during 1992 to 2009 in each month.

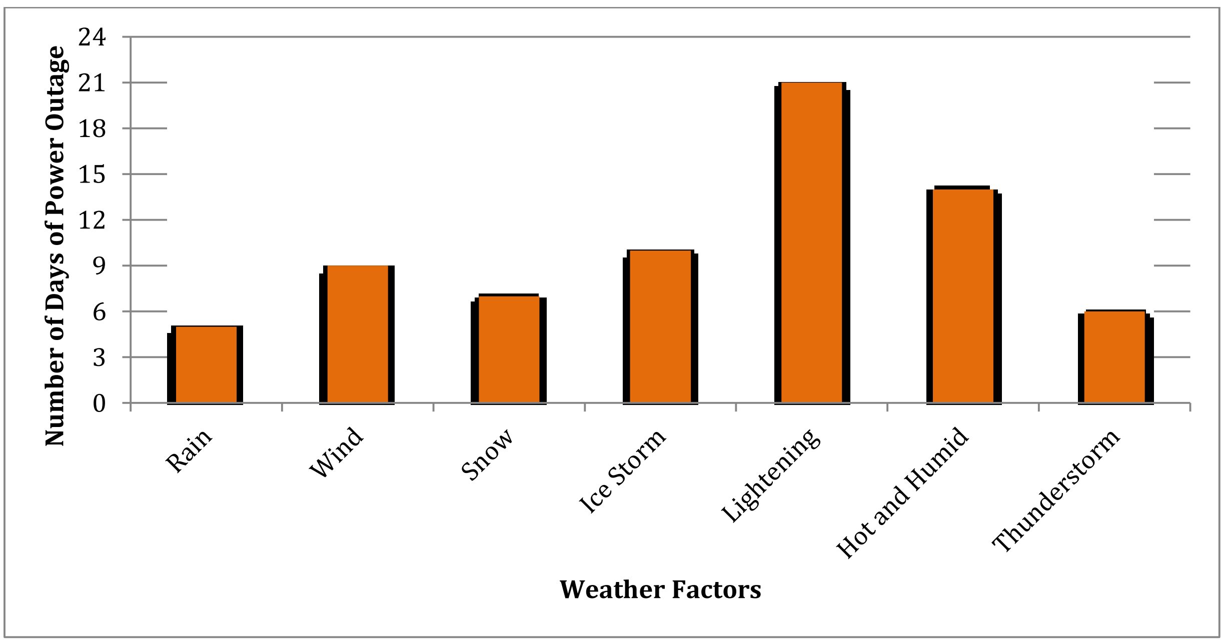


Figure 4-6. Comparison of Effective Weather Factors in Electric Power Outages during 1992 to 2009

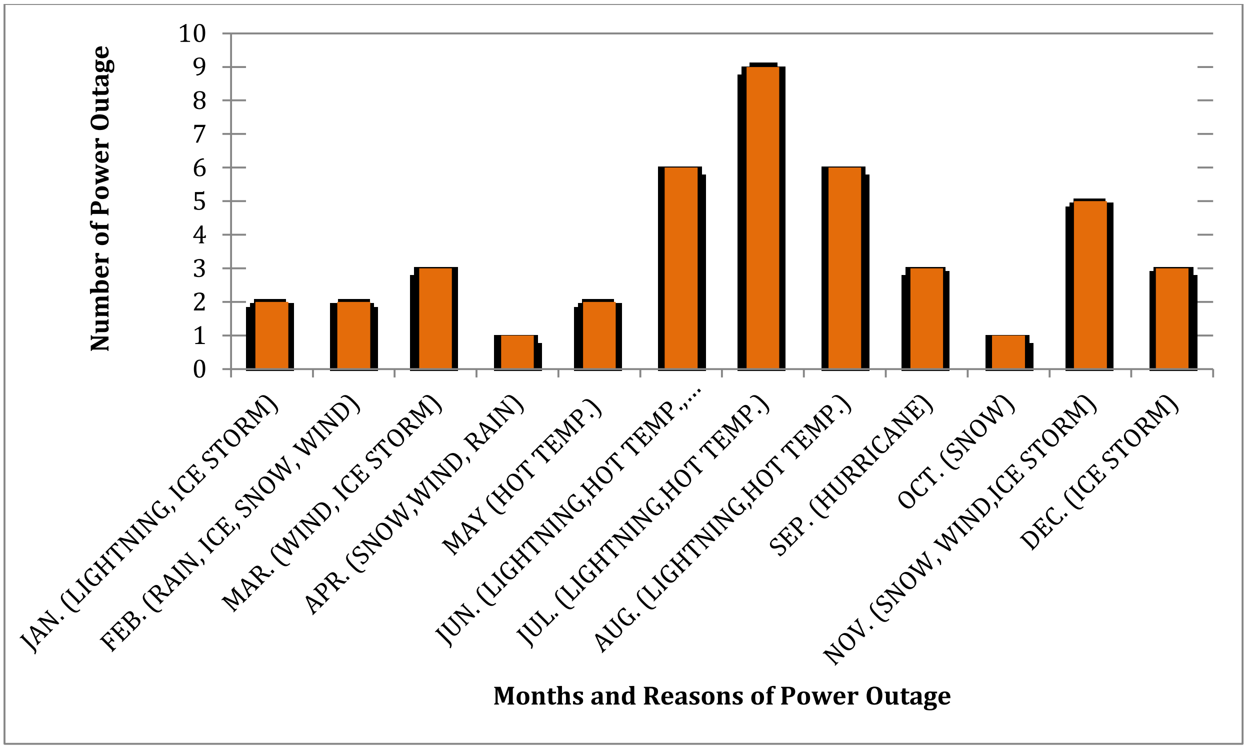


Figure 4-7. Frequency of Power Outage and their Reasons in Different Months

This research aims to develop an intelligent system that is able to find the likelihood of power outage based on the weather forecasted data. Data for weather variables are collected from the historical data provided by "Canadian Climate Data - Environment Canada", showing in Figure 4-8. The days with power outage are identified from the system disturbances reports. To realize the difference among the weather conditions of the day that power outage had happened and normal weather condition of the same day, toward each day of power outage, the weather conditions for the same day are collected for all the years between 1992 and 2009. There are 38 days of power outage caused by weather circumstances. According to the procedure of data collection, information for 646 days is gathered (38 days × 17 years). Checking and removing missing data reduce the final number of days to 614, and for each day values for five weather variables are collected. Table 4-3 shows a sample of data collection in Quebec, which shows the collected weather variables for 6th of June during 1992 to 2009.

Figure 4-8. A Sample of Data Collection of Weather Variables - Environment Canada

Table 4-3. Sample of Data Collection in Quebec for 6th of June during 1992 to 2009

Date	Wind Speed (km/hr)	Temperature (ºC)	Precipitation (mm/s)	Humidity (%)	Lightning
6/6/1992	24	10.7	0.0001	90	0
6/6/1993	19	8.3	0	77	0
6/6/1994	28	12	0.0004074	47	0
6/6/1995	28	2.1	0.0003148	38	0
6/6/1996	24	4.1	0	31	0
6/6/1997	17	5.5	0	63	0
6/6/1998	22	5.1	0	61	0
6/6/1999	37	11.70	0.0001944	46	0
6/6/2000	30	1.2	0	36	0
6/6/2001	20	8.8	6.667E-05	81	0
6/6/2002	22	7.3	0	77	0
6/6/2003	32	0.8	0.0002302	34	0
6/6/2004	28	6.7	0	39	0
6/6/2006	19	10.9	0	69	0
6/6/2007	31	24.8	0	98	0
6/6/2008	32	20.5	0	87	0
6/6/2009	35	23.9	0.0002962	91	0

There are two types of dataset collected in this stage. Dataset I consists of the extreme value for all the weather variables in each day, i.e. extreme value for all the variables in one day might not happen at the same time. Both literature review and sensitivity analysis in chapter 5 indicate that wind speed is the most critical factor to which the electric power grid is more sensitive. As a result, to examine the impact of wind speed and its effect on the electric power outages, another sets of data is collected. Dataset II consists the extreme value for wind speed, and other variables values in the same hour that wind speed reached its extreme value. Complete datasets I & II are provided in APPENDIX I.

4.2.2 Electrical Energy Consumption

Energy consumption is the delivered energy consumed at the facility level (ICF International, 2007). Energy consumption is another important factor that has effect on the likelihood of occurrences of power outages. Any place where people live is surrounded by residential and commercial buildings, which need to consume energy for heating, cooling, lightning, etc. Energy consumption varies with weather conditions (i.e. public appeal for electricity in cold seasons or warm seasons are different), geographical location (i.e. daylight hours changes with the different geographical location of cities), national events (New Year event in winter and entertainment festivals in summer can make changes in the electrical energy consumption index), etc.

To make sure that the developed model will perform accurate results, energy consumption index is also considered as input variables. These data are collected from “Electric Power Statistics – Statistics Canada”. Figure 4-9 indicates the overall energy generation and consumption in Canada during 2011 to 2014. Since this diagram follow a sinus path in different years, the average of the monthly energy consumption, which are provided in Table 4-4, can be used for training the model.

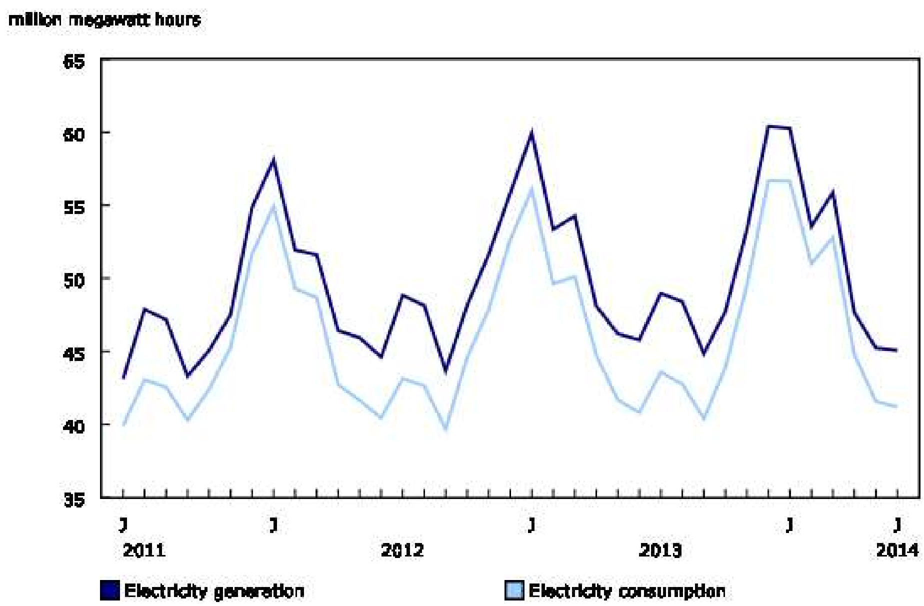


Figure 4-9. Electricity Consumption and Generation in Canada during 2011 to 2014 (Statistics Canada, 2014)

In Figure 4-9, the vertical axis is "million megawatt hours" and horizontal axis shows years. As it is indicated, energy generation rate is always higher than energy consumption index. Moreover, Table 4-4 indicates that energy consumption index increases in cold seasons.

Table 4-4. Average of Electricity Generation and Consumption

Month	Energy Consumption Index
January	1
February	0.89750592
March	0.88603677
April	0.77771709
May	0.75805571
June	0.73620972
July	0.78536319
August	0.77607865
September	0.72255598
October	0.81176042
November	0.87129073

December	0.95831058

4.2.3 Electrical Network Size

An electrical network is made of electricity generation stations, transmission and distribution lines, all of which are responsible of delivering electricity from suppliers to consumers (Kaplan, 2009). As the size of the electric power grid increases, its maintenance becomes more complicated and the likelihood of occurrences of power outage is expected to grow. Investigation in system disturbances reports between 1992 and 2009 indicate that the numbers of power outages in various provinces are different (Figure 4-10).

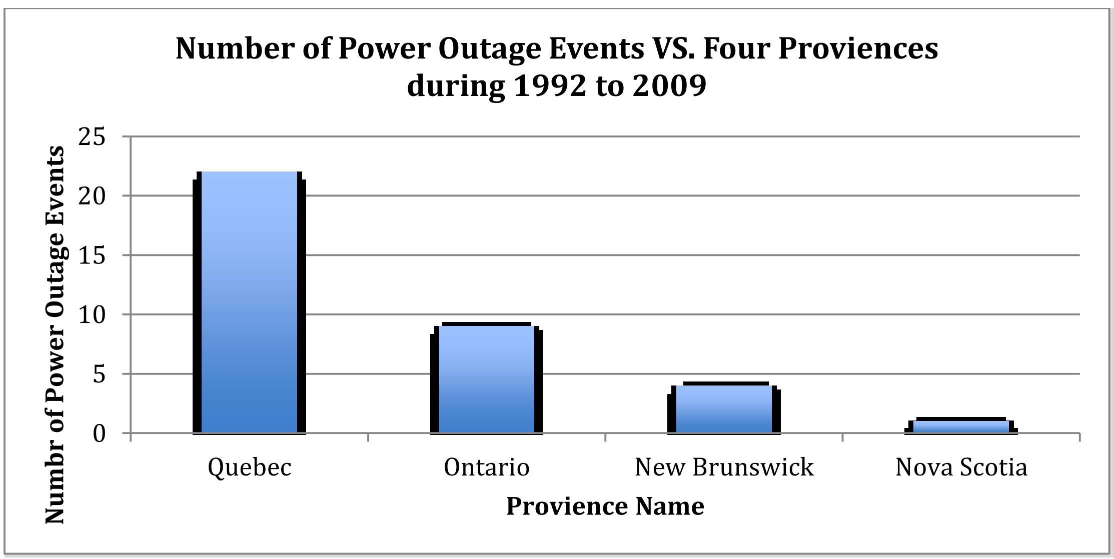


Figure 4-10. Number of Power Outage Events vs. Different Provinces during 1992 to 2009

As it is illustrated in Figure 4-10, numbers of blackout incidents in Quebec are significantly more than other provinces. In addition, Quebec generates the greatest amount of electricity in the entire of Canada, and has the largest electric network. Based on the hydro companies' reports, electricity network size for the different provinces are collected. Quebec power network size is about 305,600 km, while for Ontario, New Brunswick and Nova Scotia are

152,000 km, 31,550 km, and 31,800km, respectively (Hydro Quebec, Power Distribution, 2015; Hydro One Inc., 2009; Legislative Assembly of New Brunswick, 2001; Nova Scotia Power, 2015). Consequently, the developed model is likely to produce more accurate results by adding electric network size as an input variable.

4.2.4 Social Cost

The study of the Natural Sciences and Engineering Research Council (NSERC) in conjunction with eight Canadian electrical utilities reflects the customers' understanding and assessment of the impact of supply interruptions on their activities that depend upon electricity and the associated costs (Wacker & Tollefson, 1994). The survey considers four sectors; i.e. residential, commercial, small industrial sectors and agriculture. The total survey sample was 11,588 users, which 4,401 were usable responses. Customers were randomly selected from utility billing records or other sources. Residential customers were those accounts considered primarily as a residence. Within the commercial, industrial, and agricultural sectors, the customers were classified according to the Standard Industrial Classification (SIC) system. This system is widely accepted by government and industry in North America. The questionnaire for each sector followed the same general progression with some differences due to the customer variations between sectors. The format and content of the cost questions reflect the ways in which electricity is used in each sector and the impacts that an interruption has on those uses. Figure 4-11, Figure 4-12, Figure 4-13 and Figure 4-14 show the customer damage function in the four categories in 1995 in Canada, which the results of Wacker & Tollefson (1994) studies.

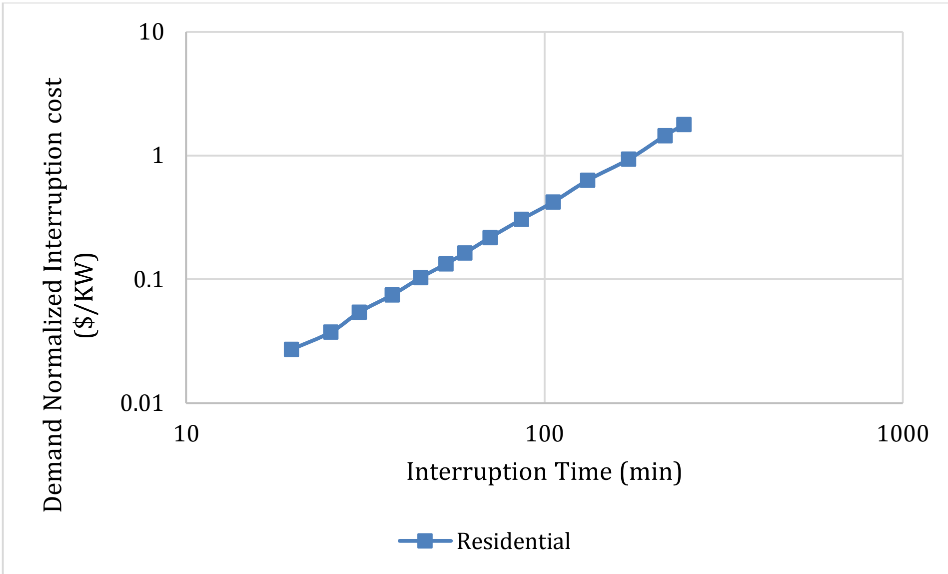


Figure 4-11. Residential Customer Damage -Costs in 1991 Canadian Dollars (Wacker & Tollefson, 1994)

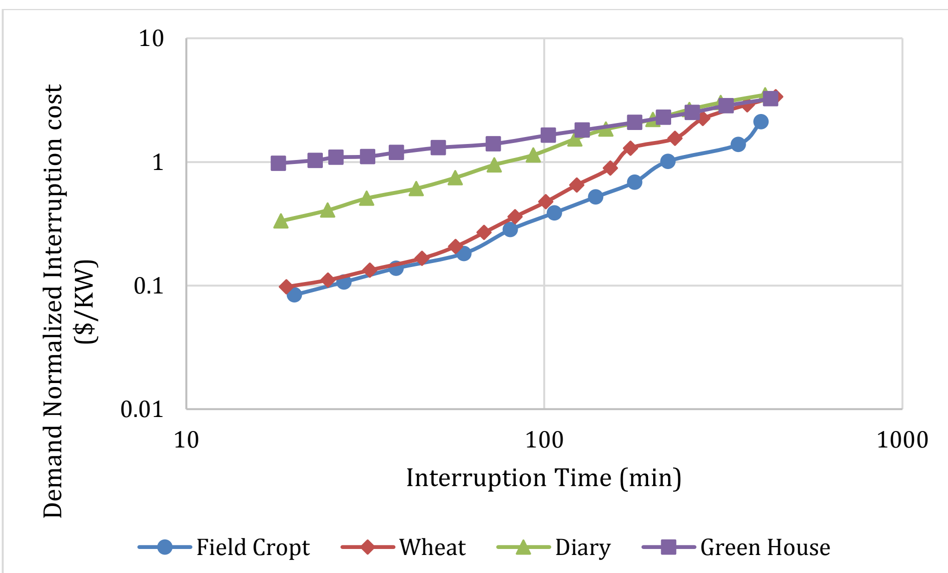


Figure 4-12. Agricultural SIC Customer Damage Functions - Costs in 1991 Canadian Dollars (Wacker & Tollefson, 1994)

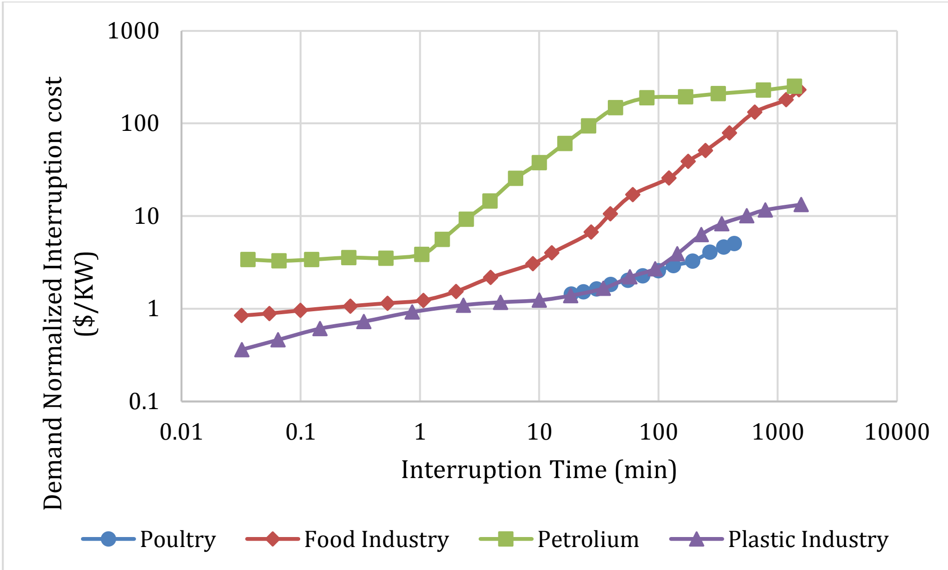


Figure 4-13. Industrial SIC Customer Damage Functions - Costs in 1991 Canadian Dollars (Wacker & Tollefson, 1994)

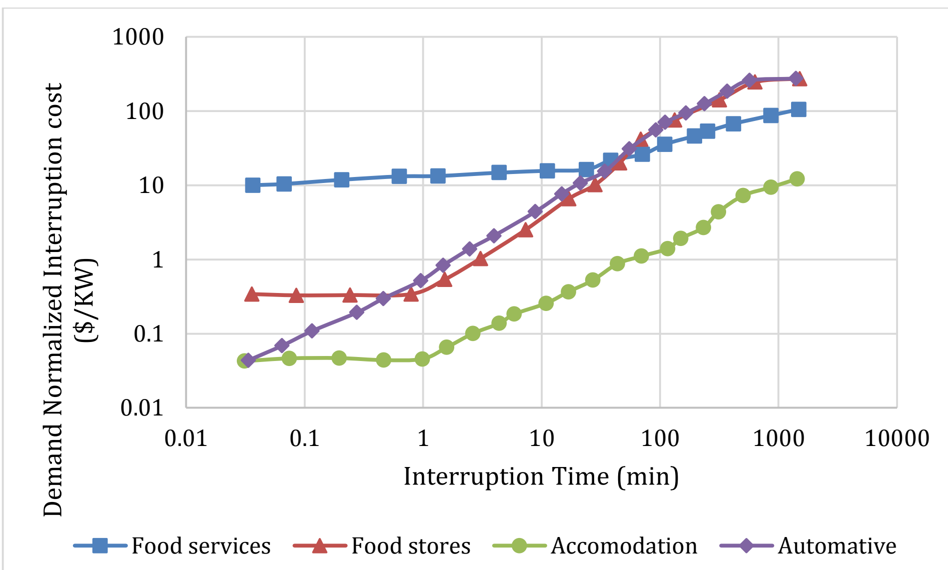


Figure 4-14. Commercial SIC Customer Damage Functions - Costs in 1991 Canadian Dollars (Wacker & Tollefson, 1994)

The data for the changes of the price of the electricity per MWh for each year up to 2010 were obtained from International Energy Agency (2012) is shown in Table 4-5.

Table 4-5. Changes of Prices for Electricity Generation in Canada during 1978 to 2010 (International Energy Agency, 2012)

Years	1978	1980	1990	2000	2007	2008	2009	2010
Canadian Dollar/MWh								
Industry Price	17.40	22.90	43.70	57.00	68.00	74.00	67.20	72.00
Household Price	27.50	33.20	62.00	78.60	95.70	96.10	96.50	97.40

To adjust the normalized data to current year (2015), changes of price in electricity consumption is considered. The nonlinear regression analysis using Gauss-Newton algorithm with aid of fit curve toolbox of the MATLAB program is used to predict the consumption price for the other years. Using Gauss-Newton algorithm, for conducting the interpolation showed that the coefficient of determination (R^2) is about 0.97 for both residential and industry. Considering the Figure 4-15, it could show that the price of the residential section increases about 53% from 1995 to 2015 and in the industrial section increases about 75% from 1995 to 2015. Commercial, industrial, and agricultural are considered as industrial electricity consumption category.

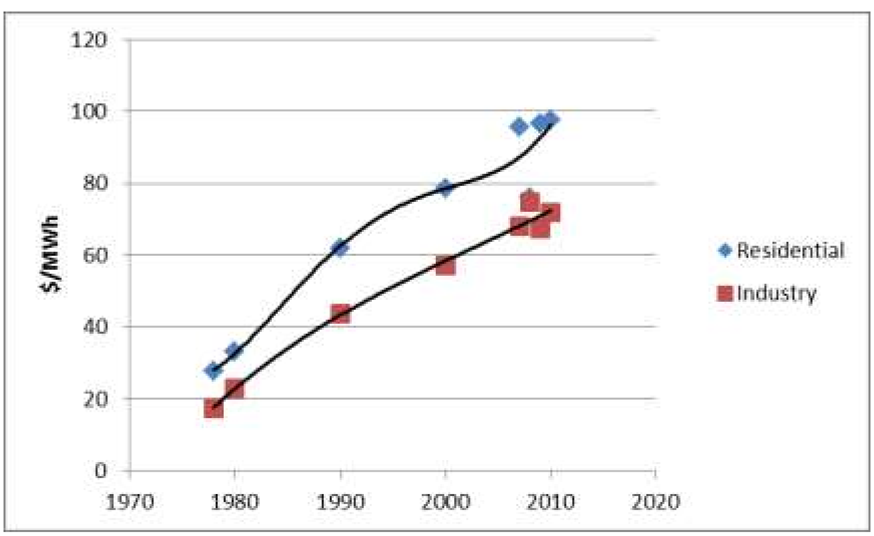


Figure 4-15. Exerted Changes electricity consumption price to 2015

For the purpose of estimating the realistic social cost of power outage, the collected data had to be updated to current prices. Based on the information provided in Figure 4-15, the social cost of power outage in 1995 are updated to 2015. Figure 4-16 indicates the updated costs in case of power failure. The horizontal axe shows the duration of the power outage, and the vertical axe shows the cost ($ CAD) per kW in case of interruption the power grids. As it is illustrated, commercial and industrial sectors have the most amount of social cost.

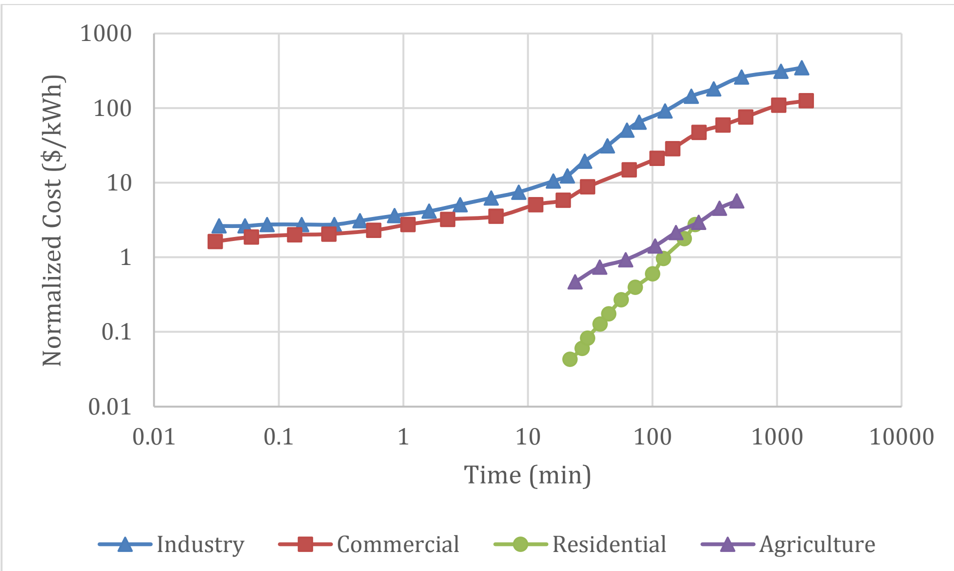


Figure 4-16. Updated Costs of Power Outage in each Sector for 2015

4.3 CHAPTER SUMMERY

This chapter includes the summery of data collecting procedure. NERC's territories consist of eight zones in the North America and require them to submit reports of any disturbances happened within the bulk electric systems in their domains. This research focuses on the Canadian are of NPCC zone, which consists of Quebec, Ontario, New Brunswick and Nova Scotia. System disturbances reports published in 1992 to 2009 are used as the main source of blackout events data for this research. Seven variables are identified as effective factors on electric power outage: weather variables (i.e. wind speed, temperature, precipitation, humidity and lightning), electricity energy consumption index and electric power networks sizes. Weather variables are collected from Environment Canada. Statistics Canada is the source of electricity energy consumption index, and electrical companies provide information about electric power networks sizes.

Two sets of datasets are collected: 1) dataset I consists of the extreme value for all the weather variables in each day, i.e. extreme value for all the variables in one day might not happen at the time, 2) Dataset II consists of the extreme value for wind speed, and other variables values in the same hour that wind speed reached its extreme value.

The social costs of electric power outage incidents in four sectors (i.e. residential, commercial, small industrial and agriculture) are collected from old customer surveys in 1995, and are updated based on the present electricity consumption price in 2015.

CHAPTER 5: MODEL DEVELOPMENT AND IMPLEMENTATION

5.1 CHAPTER OVERVIEW

In this chapter, the methodology proposed in chapter 3 is implemented and applied to the case study in order to verify the applicability of the developed model. As explained in the previous chapter, the dataset is gathered from the NERCs' system disturbances reports, Environment Canada, Statistics Canada and Hydro Companies. The dataset consists of seven quantitative variables (i.e. temperature, wind speed, humidity, precipitation, lightning, electricity consumption and electricity network size) that affect the probability of power outage.

With respect to the methodology, implementation of the framework involves five main phases. The first phase is to train BPNN model between input variables and power outage index. In the second phase, sensitivity analysis is performed to find the factor, to which the model is more sensitive. The third phase is to implement another BPNN model with a refined dataset based on the results of the sensitivity analysis. The fourth and fifth phases are modeling of the same datasets by GRNN and PNN models, respectively. Figure 5-1 illustrates aforementioned phases and how they are correlated to the defined objectives.

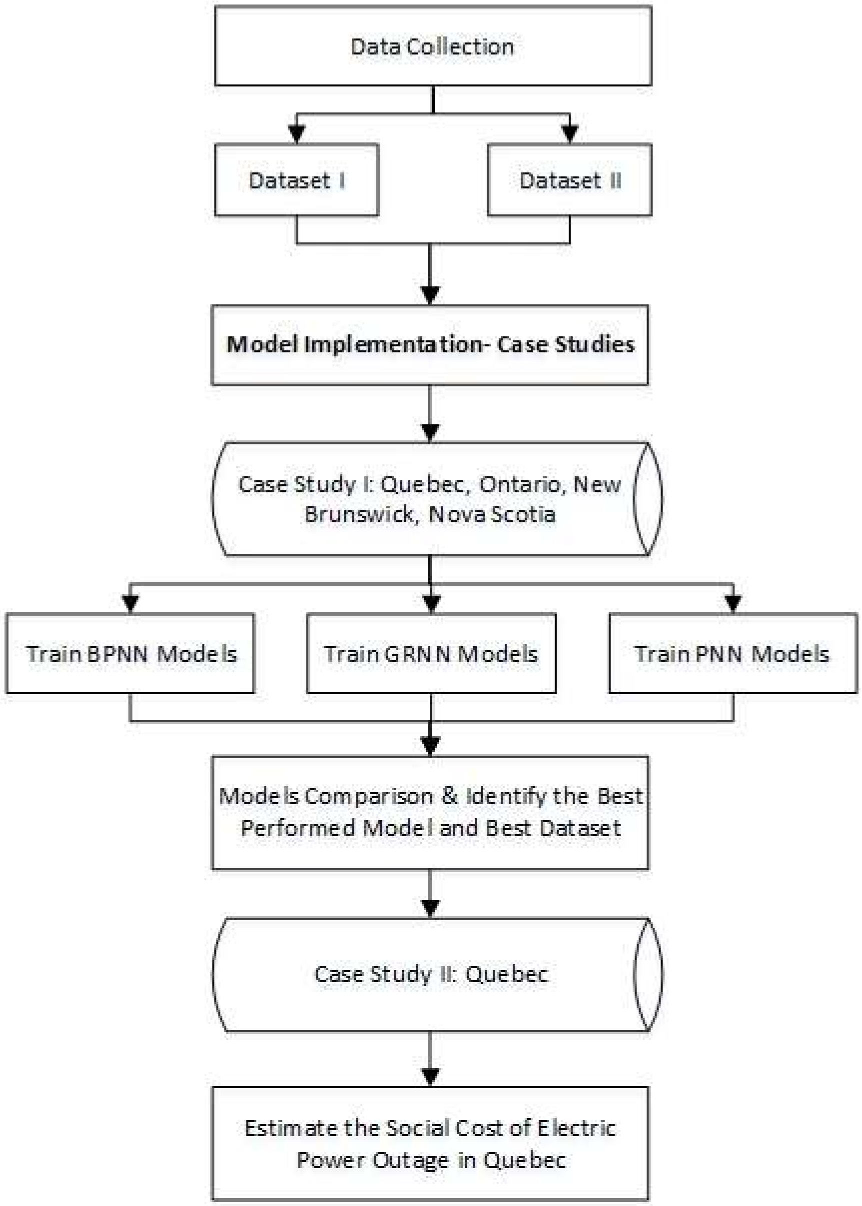


Figure 5-1. Chapter 5 Overview

5.2 TRAINING BPNN- DATASET I

As explained in chapter 4, the dataset consists of seven variables, e.g. Temperature, Humidity, Wind Speed, Precipitation, Lightning, Electricity Consumption index and Electricity Network Size. Table 5-1 presents a sample of data points for selected variables. It is assumed that power outages caused by weather conditions are affected by all these variables. Therefore, the main idea is to develop a model in order to connect the input data space to the output data space based on the logical correlations extracted from the historical data.

Table 5-1. A Sample of Data

Electricity Consumption Index	Electricity Network Size (km)	Wind (km/hrs.)	Temperature (^{o} C)	Precipitation (mm/s)	Relative Humidity (%)	Lightning
0.87129	305600	9.0	3.60	0.00017	93	0
0.87129	305600	28.0	5.90	0.00036	97	0
0.73621	305600	37.0	11.70	0.00019	46	0
0.73621	305600	24.0	13.70	0.00035	91	0
0.73621	31550	32.0	4.90	0.00000	64	0
0.78536	31550	13.0	14.80	0.00016	60	0
0.77608	305600	28.0	17.70	0.00107	61	1
0.77608	305600	20.0	14.70	0.00000	51	0
0.77608	305600	22.0	11.90	0.00000	55	0
0.89751	305600	28.0	-0.60	0.00000	99	0
0.77608	305600	19.0	9.80	0.00000	35	0
0.77608	305600	17.0	16.90	0.00000	73	0
0.72256	305600	78.0	18.60	0.00264	92	1
0.72256	305600	37.0	14.80	0.00091	97	0
0.88604	31550	57.0	-3.00	0.00013	81	0
0.88604	31550	39.0	-16.60	0.00083	76	0
0.77608	305600	22.0	7.00	0.00013	44	0
0.77608	152000	17.0	14.30	0.00000	83	0
0.72256	152000	22.0	5.50	0.00010	66	0

The first step starts with dividing the datasets, i.e. dataset is randomly divided into two sections of train data and test data. The first dataset which was collected in the dataset I (refer to CHAPTER 4: DATA COLLECTION) is used in this step. 15% of the complete data is put aside for validation of the model (called as test data), while it is trained with the rest 85% of the dataset (called as train data). 70 percent of train data is used to train the network and the remaining 30 percent are used for testing, i.e. validation (Figure 5-2). The *Bayesian*

Regularization is selected as the training algorithm. The MATLAB code for this training process is available in APPENDIX II. After several trial and errors, a network with three layers shows the best performance. The network consists of 7 neurons in the input layer and 15 neurons in the hidden layer. Figure 5-3 schematically depicts this structure.

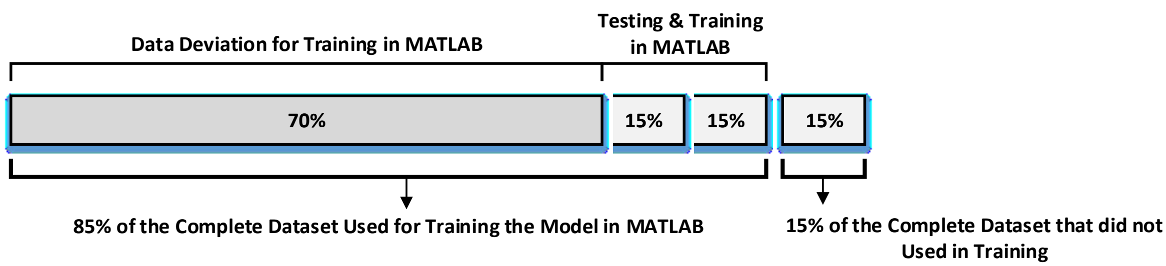


Figure 5-2. Dataset Distribution

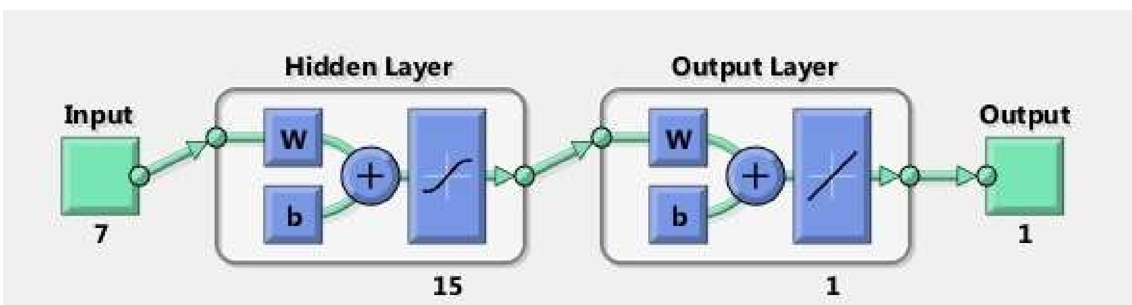


Figure 5-3. Structure of the Membership ANN

BPNN model is trained and Figure 5-4 shows the regression diagram of the trained model. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1 indicates that the regression line perfectly fits the data (Glantz, 1990). MATLAB results show that calculated R^2 for training process is equal to 0.97022.

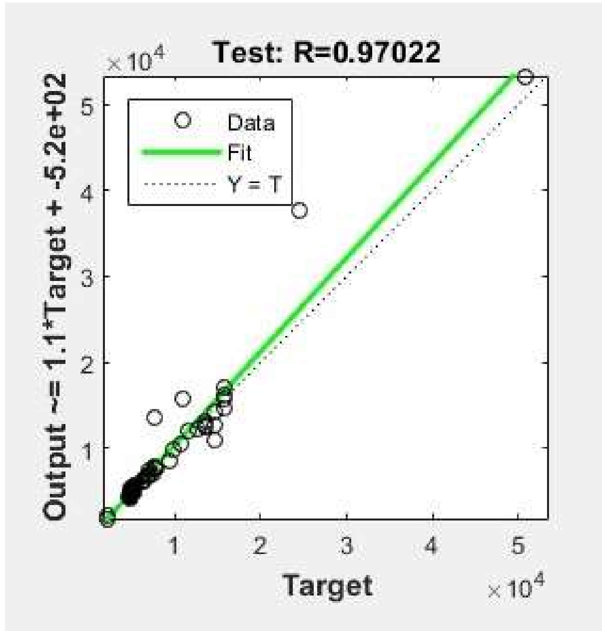


Figure 5-4. Plot Regression

Figure 5-5 indicates the information related to the training task. According to the results, the training stops at the MSE of 1.58 e-7.

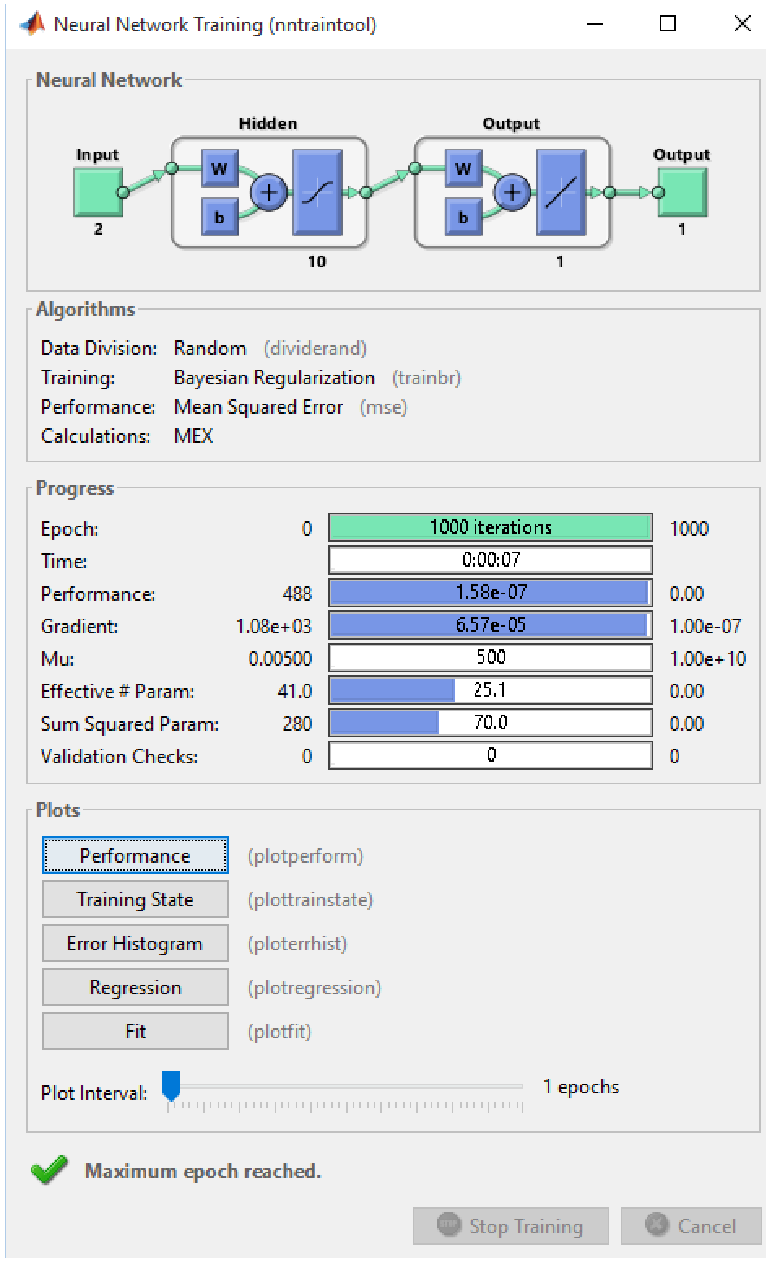


Figure 5-5. Reported Information of the Training Procedure

5.3 MODEL VALIDATION

Within model validation step, the test data, which was 15 percent of the whole data, is used to validate the model. The test dataset consists of 92 data points which were not involved in the training procedure. These data points are fed to the model as the inputs to produce predicted outputs. The actual and predicted outputs are then compared with each other.

Figure 5-6. Actual vs. Predicted Outputs - BPNN Model with Dataset I indicates the comparison between the outputs. The horizontal axis shows number of the days and the vertical axe indicates probability of the power outage (i.e. number 1 shows power outage happened and 0 means no power outage). Table 5-2. Mathematical Model Validation- BPNN Model with Dataset I also shows the amount for RMSE, MSE and R^2 of the test data, which are used to validate the model. As the RMSE and MAE are closer to zero, the model is more accurate, while as the R^2 is closer to 1, the regression line approximates the real data points better.

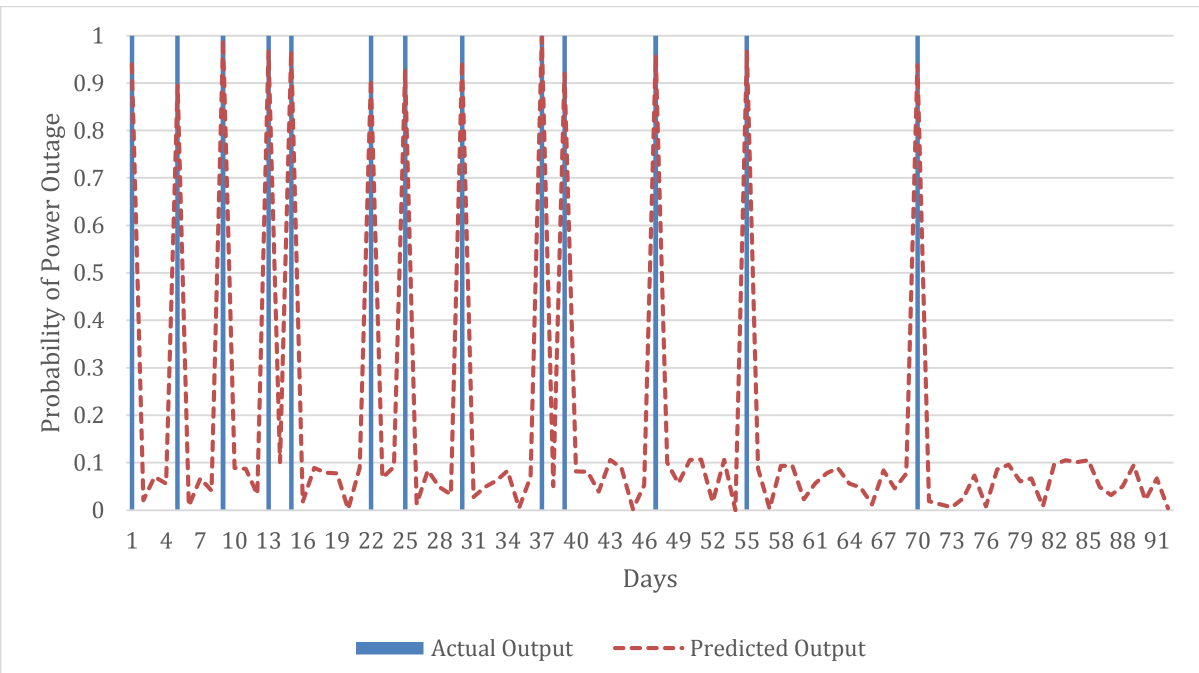


Figure 5-6. Actual vs. Predicted Outputs - BPNN Model with Dataset I

Table 5-2. Mathematical Model Validation- BPNN Model with Dataset I

RMSE	MSE	R^2
0.062	0.0522	0.960

5.4 SENSITIVITY ANALYSIS

In sensitivity analysis, one model parameter is changed at a time while the remaining model parameters are set to fixed values. To start, the difference between the minimum and maximum values of all the variables are calculated. Afterwards, the difference is divided to ten to be added to the minimum value of each variable in ten steps to reach the maximum value of that variable. Other factors take the average value of their range in historical data. Each of those ten increments accompanied with the average values of other factors are fed to the model to generate a corresponding set of outputs.

This cycle will be repeated for other factors and the results are compared to identify the variable that is comparatively important and causes a huge change in the model's behavior. Table 5-3 indicates a sample dataset prepared for sensitivity analysis. Full sets of data is available in APPENDIX I.

Table 5-3. A Sample of Data Preparation for Sensitivity Analysis

Electricity Consumption Index	Electricity Network Size	Wind	Temperature	Precipitation	Lightning	Humidity
0.72255598	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.750300382	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.778044784	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.805789186	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.833533588	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.86127799	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.889022392	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.916766794	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.944511196	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.972255598	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
1	231307.99	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	31550	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	58955	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	86360	36.483	10.21859706	0.000132589	0.231647635	91.63784666

0.827594901	113765	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	141170	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	168575	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	195980	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	223385	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	250790	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	278195	36.483	10.21859706	0.000132589	0.231647635	91.63784666
0.827594901	305600	36.483	10.21859706	0.000132589	0.231647635	91.63784666

Figure 5-6 shows the final diagram of sensitivity analysis. It could be concluded that the model is more sensitive to wind speed and less sensitive to humidity. Precipitation, temperature and electricity consumption also have a significant effect on the model. Both the minimum and maximum values of temperature can create a risky situation for the power grids. Cold weather can cause ice rains and snowfalls and increase the public electricity consumption, once the hot weather can increase the number of lightning and the public electricity consumption.

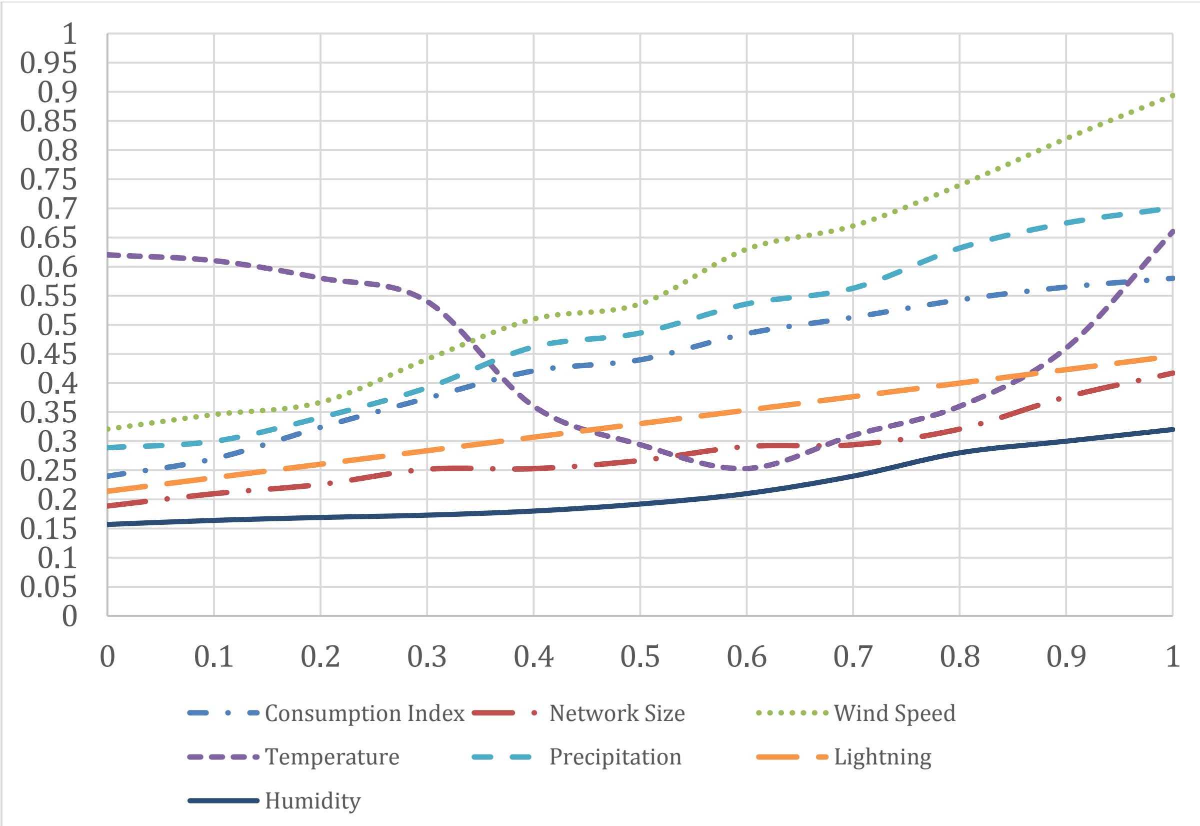


Figure 5-7. Sensitivity Analysis: Power Outage Probability vs. Different Factors

To identify how wind speed is important in probability of power outage and how it can affect the results of the model, a new set of data is collected (Dataset II), i.e. the extreme value of the wind speed is identified, and values of other weather factors are collected at the same hour that wind reaches its maximum speed. The full dataset is provided in APPENDIX I. To identify which dataset provides more accurate results, a new BPNN model is developed with the new datasets. In addition, GRNN and PNN models are developed with both datasets I & II. The best model and datasets are expected to be used for a narrowed down case study in Quebec.

5.5 TRAINING BPNN- DATASET II

A new BPNN model with the same architecture as the one explained in Section 5.2 is developed with the new dataset (i.e. seven factors as the input variables and fifteen neurons in the hidden layer. Also, the dataset distribution is the same as before). The dataset II consists of the extreme value for wind speed, which is the most effective factor in power outage incidents, and other weather factors at the same time as the wind reaches its extreme value. The actual and new predicted outputs are compared with each other. Figure 5-8 indicates the comparison between the outputs. Table 5-4 also shows the amount for RMSE, MSE and R^2 of the test data, which are used to validate the model.

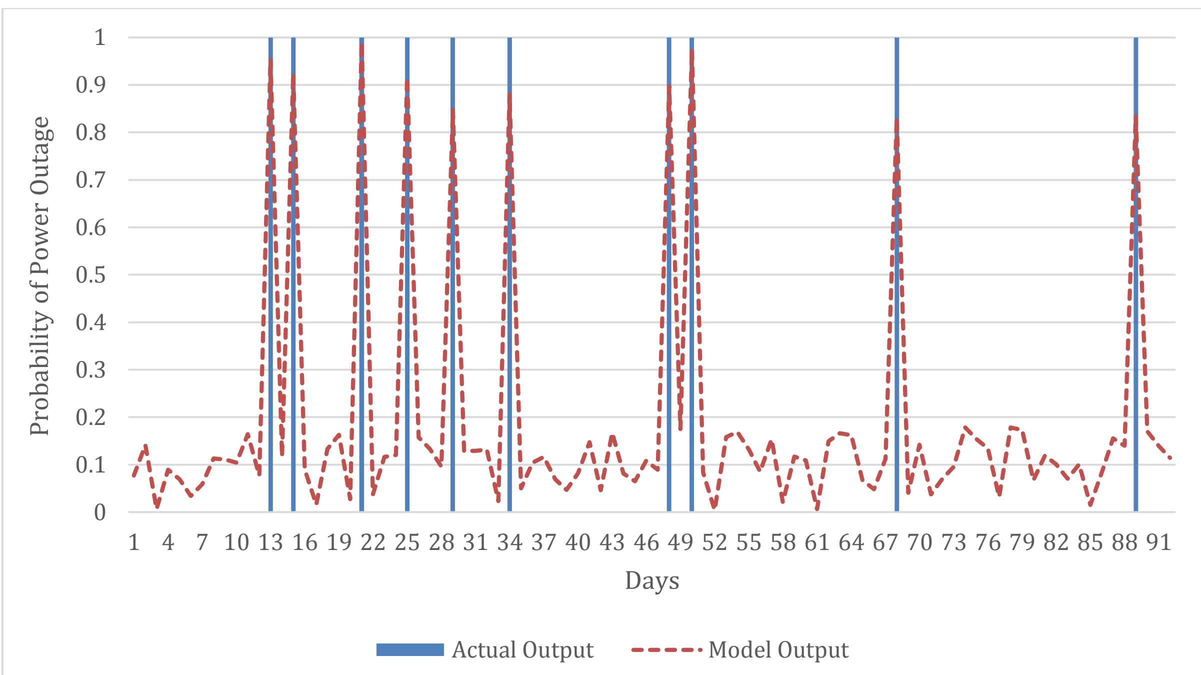


Figure 5-8. Actual vs. Predicted Outputs - BPNN Model with Dataset II

Table 5-4. Mathematical Model Validation- BPNN Model with Dataset II

RMSE	MSE	R^2
0.0631	0.0558	0.9477

RMSE, MSE, and R^2 are used to compare between results of the BPNN models, showing in Table 5-5. As it is illustrated, R^2 in the model developed with datasets is I closer to 1. Also, both RMSE and MSE values in the first model is closer to 0, which means the model using datasets I provides more accurate results.

Table 5-5. Comparison between BPNN Models Developed by two Datasets

	RMSE	**MSE**	**R^2**
BPNN Model- Dataset I	0.0620	0.0522	0.9604
BPNN Model- Dataset II	0.0631	0.0558	0.9477

In the next step, GRNN and PNN models are developed with the same approach about the datasets. The results for each model are compared with each other. In the last step, the best type of model and datasets that can provide the most accurate results are chosen.

5.6 TRAINING GRNN DATASET I & II

GRNN is a three-layer network with one hidden layer. GRNNs are known for their ability to train quickly on sparse data sets (Specht D. F., 1991). Unlike the BPNN, similar to PNN, the design of the GRNN is straightforward and does not depend on training parameters, but a smoothing factor is applied after the network has been trained (Demuth and Beale, 1998; Sinha and Pandey, 2002). The distribution of datasets used for training the GRNN is the same as BPNN (i.e. 85 % of the dataset are for training the model in the MATLAB, and 15 % of the dataset is used for testing the model after training part is over). Also, the architecture of the model is the same as BPNN model (i.e. seven factors as inputs and fifteen neurons in one hidden layer).

Figure 5-9 and Figure 5-10 indicate the comparison of the actual and predicted outputs of the both developed models. Table 5-6 also shows numerical comparison. As it is indicated in the tables the GRNN model using the dataset I provide a more accurate results

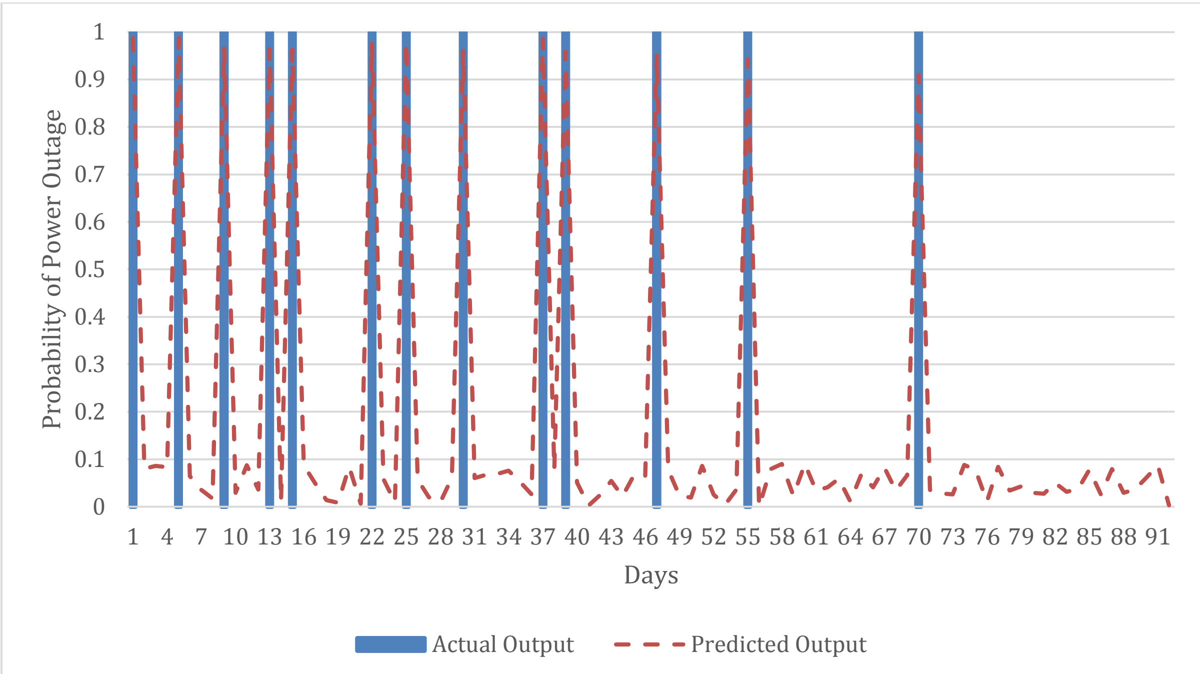


Figure 5-9. Actual vs. Predicted Outputs - GRNN Model with Dataset I

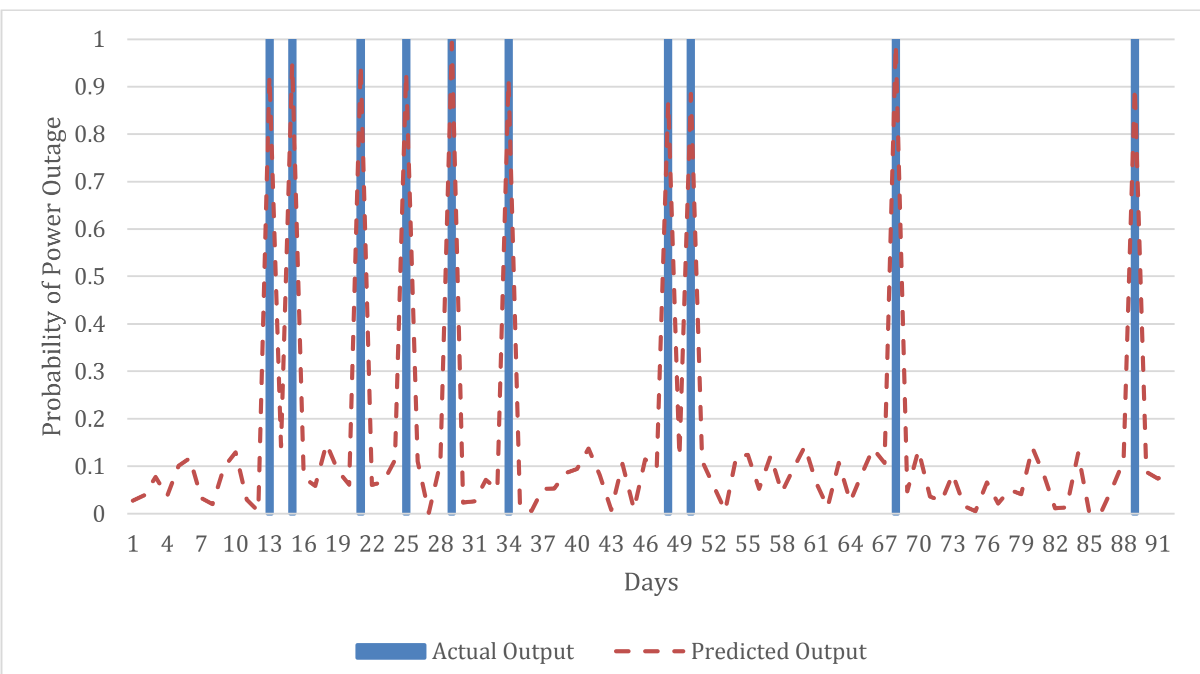


Figure 5-10. Actual vs. Predicted Outputs - GRNN Model with Dataset II

Table 5-6. Comparison between GRNN Models Developed by two Datasets

	RMSE	MSE	R^2
GRNN Model- Dataset I	0.0493	0.0431	0.9760
GRNN Model- Dataset II	0.0605	0.0522	0.9528

5.7 TRAINING PNN DATASET I & II

Design of the PNN model is similar to GRNN model. The distribution of datasets used for training the model is the same as BPNN (i.e. 85 % of the dataset are for training the model in the MATLAB, and 15 % of the dataset is used for testing the model after training part is over). Also the architecture for the model is the same as BPNN model (i.e. seven factors as the inputs and fifteen neurons in one hidden layer). The MATLAB code written to run the model is provided in the Appendix.

Figure 5-11 and Figure 5-12 indicate the comparison of the actual and predicted outputs of the both developed models. Table also shows numerical comparison. As it is shown in the table 5-7, the PNN model using the dataset I provides a more accurate results.

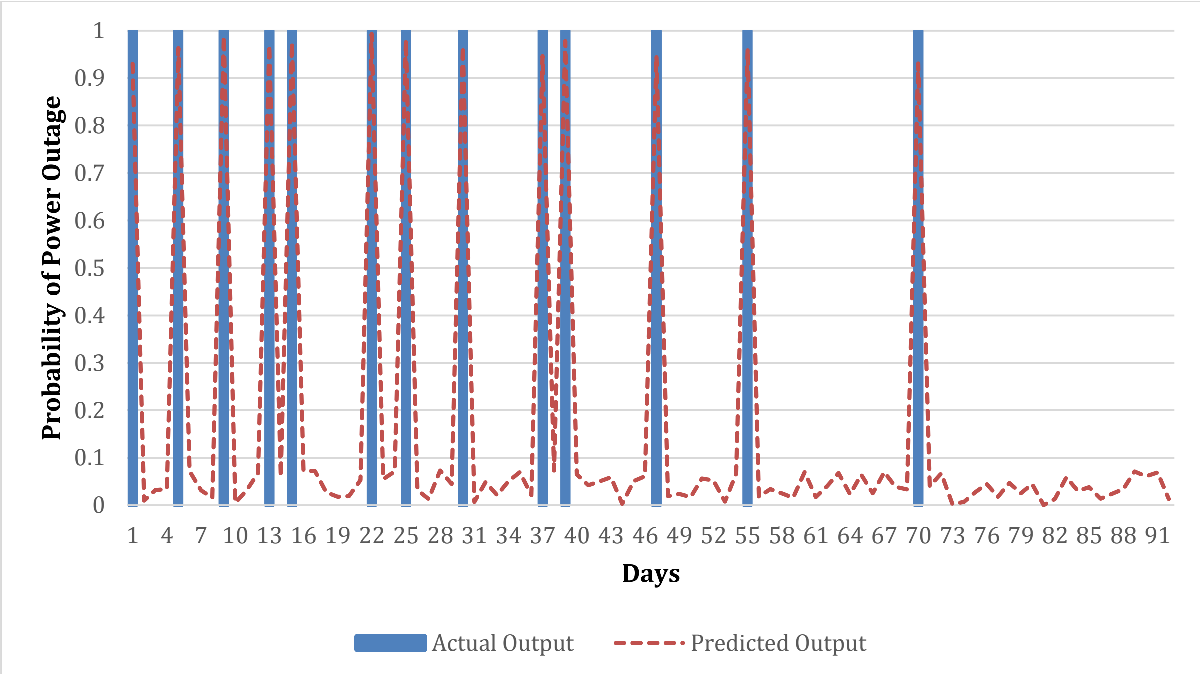


Figure 5-11. Actual vs. Predicted Outputs - PNN Model with Dataset I

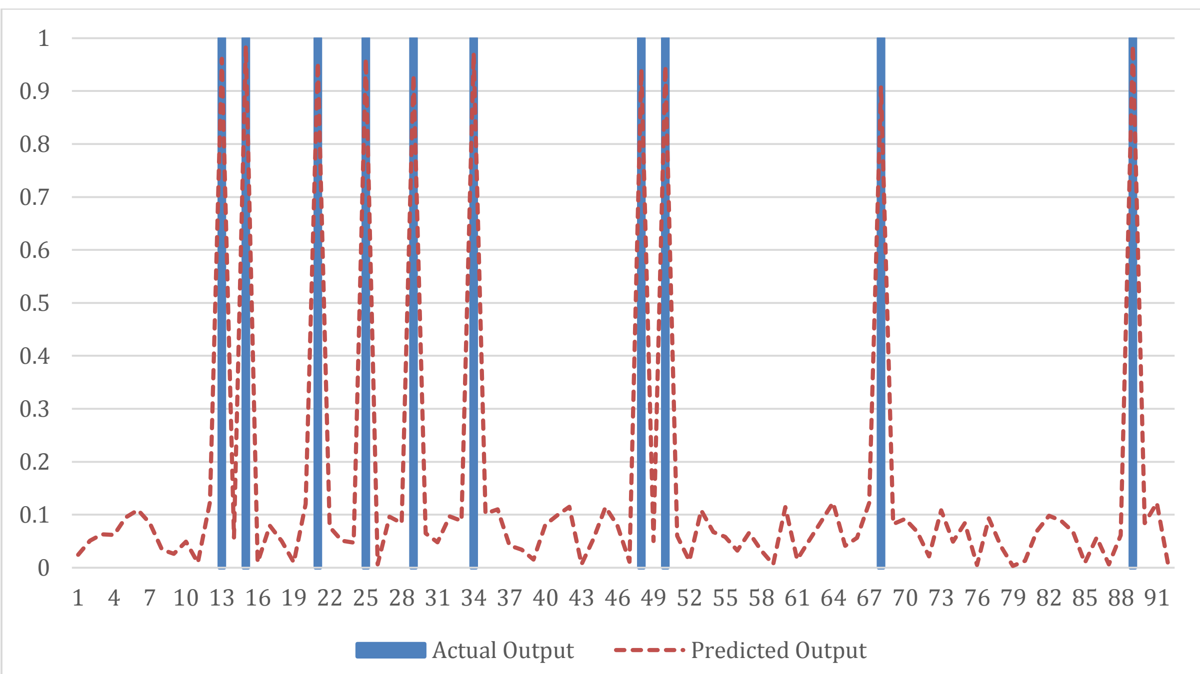


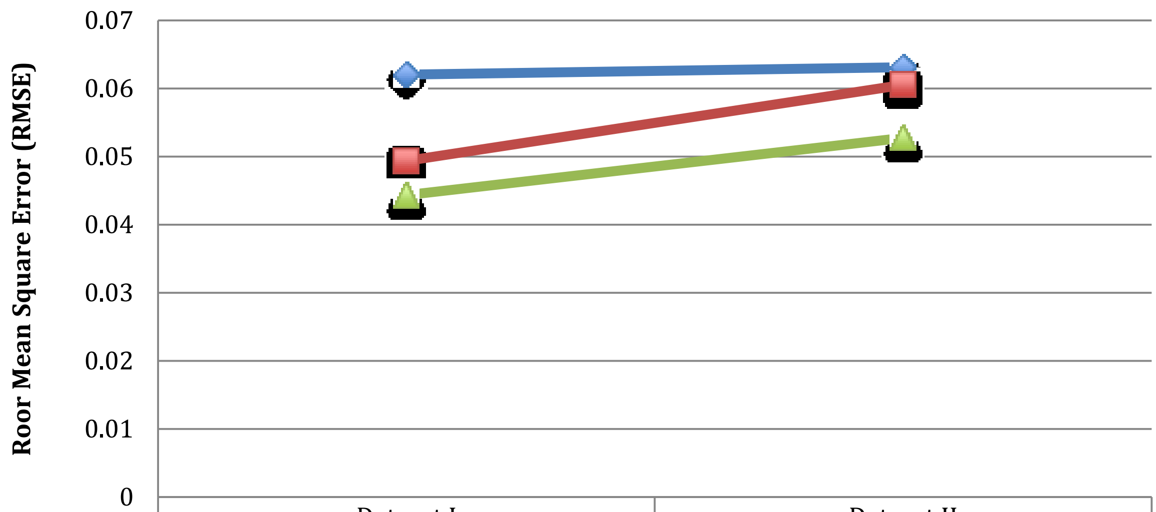
Figure 5-12. Actual vs. Predicted Outputs - PNN Model with Dataset II

Table 5-7. Comparison between PNN Models Developed by two Datasets

	RMSE	MSE	R^2
PNN Model- Dataset I	0.0443	0.0388	0.9810
PNN Model- Dataset II	0.0527	0.0449	0.9655

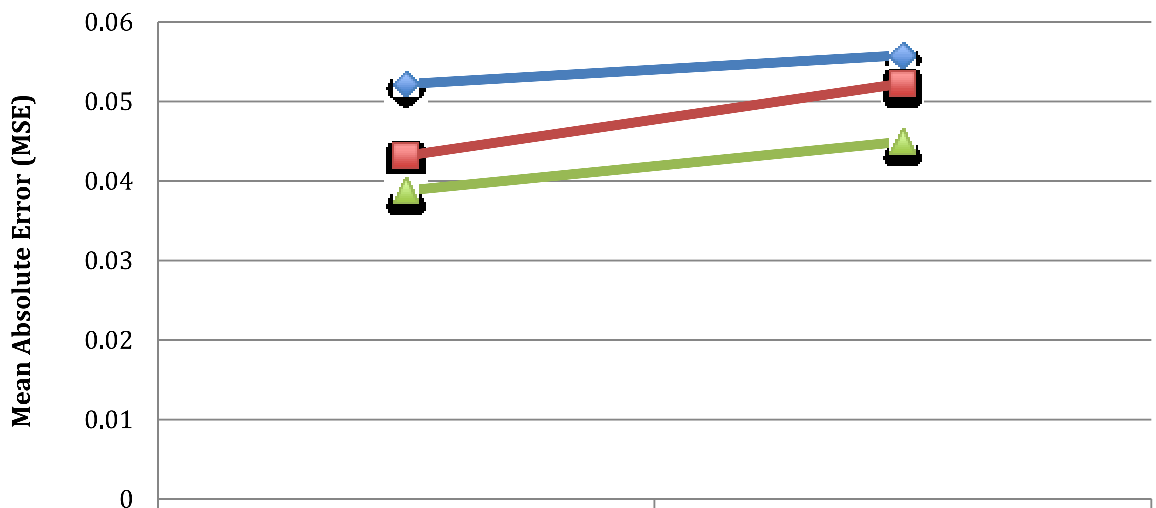
5.8 RESULTS AND COMPARISON

The development of the proposed NN models was performed using MATLAB Neural Network Toolbox (Demuth and Beale, 1998). In this section, comparison between the presented models and their results are discussed. For comparison purposes, values for R^2, RMSE and MSE are calculated using the test dataset, which was 15% of the whole data set, randomly selected without any contribution in training procedure. The comparison is conducted along two steps; first stage is to find the best dataset (i.e. dataset I or dataset II) that provides more accurate results, and second stage is to find the best performing NN model. The results of the analysis are shown in Figure 5-13, Figure 5-14 and Figure 5-15 and. Dataset I, which consists of the extreme values for all the weather factors, generates more accurate results.



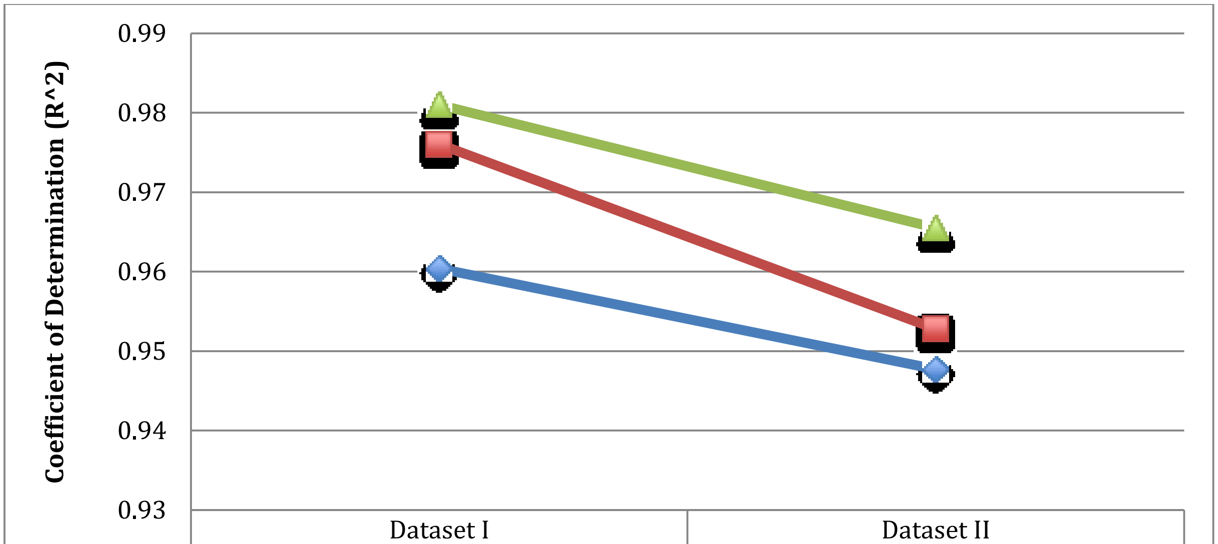
	Dataset I	Dataset II
BPNN	0.06202	0.06312
GRNN	0.04934	0.06054
PNN	0.04431	0.05275

Figure 5-13. RMSE Comparison for Different NN Models



	Dataset I	Dataset II
BPNN	0.0522	0.0558
GRNN	0.04316	0.05227
PNN	0.0388	0.04494

Figure 5-14. MAE Comparison for Different NN Models



	Dataset I	Dataset II
BPNN	0.9604	0.9477
GRNN	0.976024	0.9528
PNN	0.981	0.9655

Figure 5-15. R^2 Comparison for Different NN Models

Figure 5-13 to 5-15 indicate that the performance of PNN and GRNN models are better than the BPNN model and are able to perform better model with more accurate results. There are no training parameters such as learning rate and momentum as there are in BPNN, but there is a smoothing factor that is used when GRNN or PNN are applied to new data. Unlike BPNNs, which propagate training patterns through the network many times seeking a lower mean square error between the network's output and the actual output or answer, GRNN and PNN training patterns are propagated through the network only once.

Once the analysis shows that the PNN model using dataset I provide better results, this approach is expected to be used for further analysis, which is case study in Quebec Province.

5.9 CALCULATE THE MODEL RELIABILITY

To find out how reliable is the model and how it is expected to work with new weather forecasting data, three ranges of thresholds are selected. Once the error of the predicted outputs are in the range of the thresholds, it is considered as a correct answer, otherwise it is considered as a wrong answer. To check the accuracy of the best performing model which was chosen in the previous section (i.e. the PNN model trained with dataset I), three thresholds of 0.02, 0.04 and 0.06 are chosen. For example in the first case, if the predicted probability of the power outage is equal or more than 0.98 for a happened power outage case or, equal or less than 0.02 for a not happened outage case, the guess will be considered as a correct one. The ratio number calculated from the number of correct predictions divided by the total number of outputs reflects the accuracy of the model. Same practice is performed for PNN model, which showed the lowest error of estimation. Below Table 5-8 tabulates the results out of this analysis. For instance, in reliability margin of 0.04 it could be interpreted as: "Accepting a 4 percent risk of error in estimation, the model provides reliable predictions in 52.17% of the cases".

Table 5-8. Calculating the Model Reliability

Thresholds of Accepted Error in the Predicted Outputs compared to Actual Outputs	**Accuracy of the Results of the Model**
$if\ \lvert Actual\ Output - Predicted\ Output \rvert \leq 0.06 \xrightarrow{yields} Accurate\ Result$	80.43 %
$if\ \lvert Actual\ Output - Predicted\ Output \rvert \leq 0.04 \xrightarrow{yields} Accurate\ Result$	52.17 %
$if\ \lvert Actual\ Output - Predicted\ Output \rvert \leq 0.02 \xrightarrow{yields} Accurate\ Result$	23.91 %

5.10 PNN MODEL FOR QUEBEC PROVINCE - DATASET I

The datasets and models developed in the previous section were all for the four eastern Canadian provinces: Quebec, Ontario, New Brunswick, and Nova Scotia. There are some attributes specific for each different region, such as consumption culture and day light duration which create some factors that were not included in the previous studies. For example, a) the culture of consuming electrical energy might be different in various provinces, e.g., bigger cities like Toronto, ON or Montreal, QC have more night lives and more electricity is consumed for restaurants and entertainments places. b) These provinces have different latitudes that can make difference in daylight hours. For example, daytime duration in Forestville, QC (48°44′0″N) and Windsor, ON (42°16′58″N) are compared with each other in Figure 5-16.

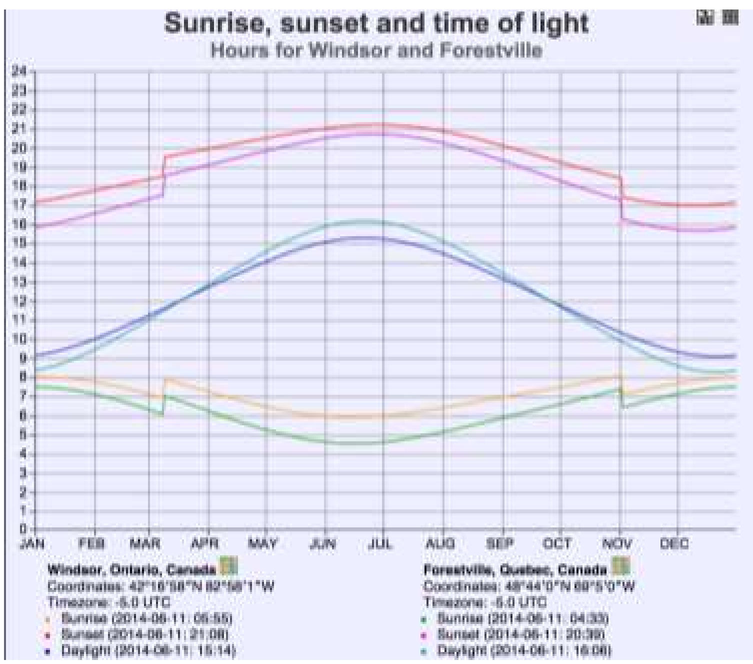


Figure 5-16. Comparing daylight between two cities: Windsor, ON and Forestville, QC (https://ptaff.ca/soleil/?lang=en_CA

Therefore, to find out if narrowing down the data and making them more uniform can cause any constructive change in the results, this research will continue to develop a model considering only the data for one province. Since the system disturbance reports show that number of power outages in Quebec has a drammatic difference with other provinces (22 days out of 38 days), data for Quebec is used as inputs for the new model.

Same as previous models, the whole data set is divided into two parts: 85% for training and 15% for testing. The complete number of data for Quebec is 381 days, divided to 323 days used as inputs for PNN model, and 58 days used for testing the developed model. The MATLAB code applied to run the model is provided in the APPENDIX II. Figure 5-17 illustrate the comparison of the actual and predicted outputs for the developed model. Table 5-9 summarizes the values for R^2, RMSE and MAE

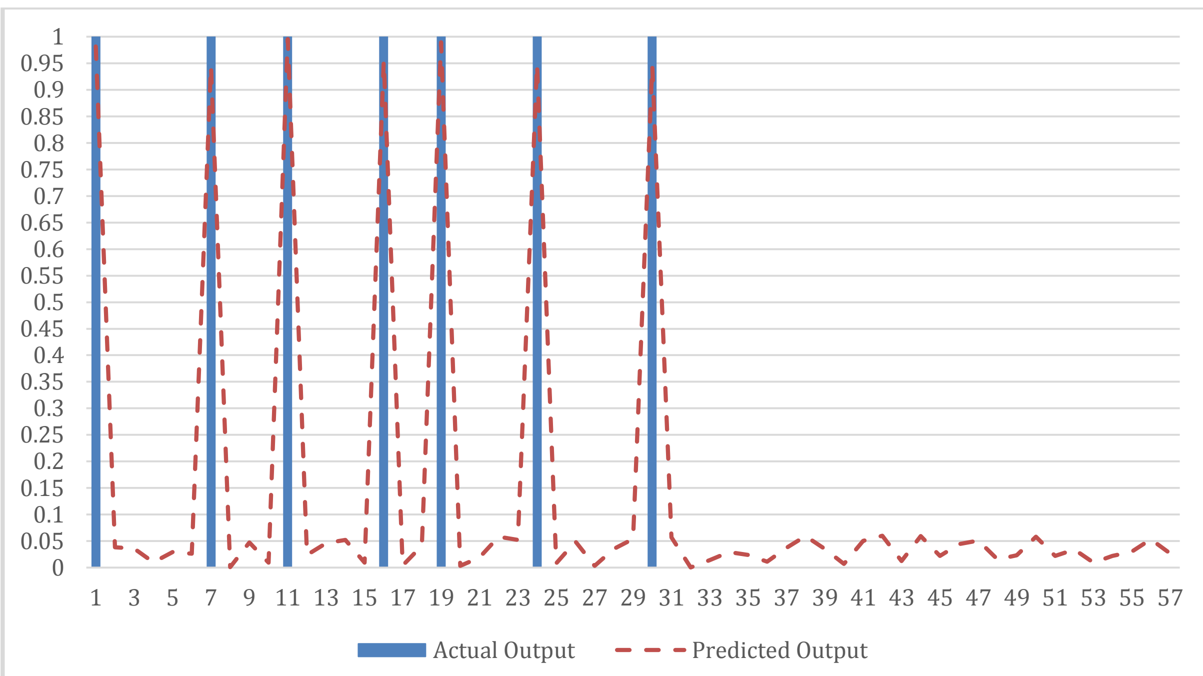


Figure 5-17. Actual vs. Predicted Outputs - PNN Model for Quebec with Dataset I

Table 5-9. Mathematical Validation- PNN Model for Quebec with Dataset I

	RMSE	MSE	R^2
PNN Model- Dataset I	0.0413	0.0355	0.984

The performance of this model shows a slight difference in the accuracy of the model. As the numbers in Table 5-8 show, the results for Quebec is more sound compared to the results of the PNN model for all four provinces. It can be concluded that, exclusive attributes of a region may have some effects on the results, and it would be better to concentrate on one specific area in each one step of modeling.

5.11 CALCULATE THE SOCIAL COST - QUEBEC

In this section, an attempt is made to estimate the social cost of electric power failure in Quebec. Once the likelihood of power failure is calculated, by identifying the average duration of power outage and the average cost for power failure per time, an estimation for social cost in different sector can be prepared.

As a result, weather varibales for one week in Janurary and June 2015 for Quebec are collected from Environment Canada (Table 5-10). PNN model is then developed with the new dataset to predict the likelihood of power failure occurance in each day. Probability of the power outage in each week of each month can be obntained by adding all the probabilities of each day of that month. According to Blackout Tracker Canada Annual Report (2014) the average duration of outage in Quebec is 32 minutes.

Table 5-10. Weather Variables for One Week in January and June 2015 in Quebec (Environment Canada, 2015)

Date	Extreme Temperature (°C)	Total Precipitation (mm)	Speed of Max Gust (km/h)	Humidity	Lightning	Likelihood of Power Outage
2015-01-10	-27.3	0.2	50	97	1	6.32
2015-01-11	-30.1	0	41	91	0	0.84
2015-01-12	-19.4	1.6	39	85	0	0.03
2015-01-13	-25	0	43	88	0	0.9
2015-01-14	-28	0	35	82	0	0.19
2015-01-15	-21.4	0	31	87	0	0.21
2015-01-16	-19.4	2.8	59	90	0	0.75
2015-06-10	22	0.2	31	91	0	0.75
2015-06-11	17.4	1.8	31	89	0	0.81
2015-06-12	18.5	0.4	31	83	0	0.47
2015-06-13	23.2	0.2	43	83	0	2.96
2015-06-14	17.4	0	50	77	0	3.46
2015-06-15	21.1	0	46	78	0	1.65
2015-06-16	24.6	5.6	41	92	0	4.87

As it was explained in chapter 4, the social cost involved in the four sectors of residential, commercial, industrial and agriculture in the entire Canada were collected from customer surveys in 1995. The numbers are then updated to the price of 2015. This research will assume that electricity consumption price in all the Canadian provinces are similar. Furthermore, it is assumed that electric power outage has happened every day for the average time of 32 minutes. Thus, that based on the likelihood of power outage occurrences in January and June in Quebec, the social cost of power outage is estimated (Table 5-11 and Table 5-12).

Table 5-11. Estimated Social Cost for Four Sector in Quebec in January 2015

Total Likelihood of Power Outage Occurrences in One Week (%)	Number of the days	Social Cost of Power Outage ($/KWh per 32 minutes)		Total Social Cost ($/KWh)
10.24	7	Residential	0.06	**4.30**

	Agriculture	0.60	**43.00**
	Commercial	7.00	**501.76**
	Industrial	20.00	**1,433.60**

Table 5-12. Estimated Social Cost for Four Sector in Quebec in June 2015

Total Likelihood of Power Outage Occurrences in One Week (%)	Number of the days	Social Cost of Power Outage ($/KWh per 32 minutes)		Total Social Cost ($/KW)
14.97	7	Residential	0.06	**6.28**
		Agriculture	0.60	**62.87**
		Commercial	7.00	**733.53**
		Industrial	20.00	**2,095.80**

As the Table 5-11 and Table 5-12 illustrate, electric power incidents are more likely to happen in June 2015 than January, thus, the expected social cost in June is additional, respectively. Moreover, Commercial and Industrial sectors would meet more social costs in the case of electric power outage occurrences. As a final point, this procedure allow the electrical companies to estimate the amount of lost money in the four sectors in advance.

5.12 SUMMERY

In this chapter, methodologies described in Chapter 3 were examined with numerical examples. Based on the datasets collected in Chapter 4, a BPNN model was trained with dataset I (i.e. the extreme value for all the weather factors). Once the errors of the model are accepted, the test dataset, which were randomly selected and didn't have any role in training, were considered as inputs for the BPNN model. The comparison between the predicted and actual outputs and mathematical validation indicate that R^2 is equal to 0.96, which is acceptable. To find out that which variable has the most effect on the model results, sensitivity analysis was performed, and the results shows that wind speed has the most effect of power outage incidents. Going back to Chapter 4: Data Collection, dataset II is collected, consisting the maximum value for wind speed and other weather factors value at the same hour as the maximum wind speed happened. Another BPNN model were then developed with the new dataset. Similarly, GRNN and PNN models were also trained with the two datasets I and II. The results showed 0.96, 0.97 and 0.98 for BPNN, GRNN, and PNN respectively in terms of R^2 with dataset I, and 0.94, 0.95 and 0.96 with dataset II. With the respect to previous arrangement, the result showed 0.062, 0.049 and 0.044 in terms of RMSE with dataset I, and 0.062, 0.06 and 0.052 with dataset II. Moreover, results for MSE shows that the dataset I for BPNN, GRNN, and PNN are 0.0522, 0.043, and 0.038 respectively for dataset I, and 0.055, 0.052, 0.044 for dataset II. Results comparison shows that dataset I in all models provided better results. In addition the trained PNN model reached more accurate results than BPNN and GRNN.

In the next stage, the best model (e.g. PNN) and best dataset (e.g. dataset I) were chosen to develop a new model only for Quebec. The results of the PNN model for Quebec, provided more accurate model; i.e. 0.041 for RMSE, 0.035 for MSE and 0.984 for R^2. It can be concluded that, once dataset get more specific for one region, model can be trained in a better way. In the next stage, social cost of electric power outage for one week in January and June 2015 were estimated for Quebec. In the case of electric power outage for one week in January 2015, the social cost would be $/KWh 57,249.55 and for one week in June 2015 the social cost would be $/KWh 92,751.71.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1 SUMMARY AND CONCLUSION

The present research proposes an intelligent model to enhance the probability of power outage incidents triggered by weather circumstances. The current research is a response to the shortcomings of electrical companies dealing with power outages, by training different types of ANN models. The proposed framework models find the effect of the weather condition variables and their relevant factors on the electrical networks to provide a model which can help electrical companies in finding the likelihood of electric power outage occurrences based on weather situations. In addition, social cost of power failure on four sectors are estimated; i.e. residential, commercial, industrial and agriculture.

First, a thorough literature review was conducted to scrutinize the shortcomings in the current area of research. It was understood that previous models used to investigate the weather disasters, which had caused blackouts before, do not display a satisfactory accuracy for the finding of the probability of power outage. ANN models are able to deal with uncertain data better and also, are can find patterns and relations among the datasets and utilize it for new set of data. In addition, seven variables were identified that are correlated to the relationship of weather conditions and power outage; e.g. temperature, wind speed, precipitation, humidity, lightning, electrical consumption index and electrical network size.

Since this research is working with weather data, which are uncertain, a set of six ANN models were trained. ANN models were trained with two sets of data, to find the most important variable effecting power outage incidents. Models were accompanied with sensitivity analysis and in addition, mathematical analysis were developed for the purpose of comparison with the best performing ANN model.

The methodology of current research encompassed six main phases, (1) training BPNN with dataset Phase I; (2) performing sensitivity analysis; and (3) training BPNN with dataset Phase II; (4) training GRNN with dataset Phase I & II; (5) training PNN with dataset Phase I & II; (6) estimating social cost of electric power outage. Sensitivity analysis in the second stage is responsible to find the most important variable to which the model is more sensitive. Once wind speed is recognized as the critical variable through sensitivity analysis, another BPNN model was developed with a new set of data. GRNN and PNN models were also trained with the two sets of data. For the purpose of comparison among the best performing ANN models and datasets, mathematical analysis were developed. Once the best performing model and best dataset is identified, case studies are developed to find both the likelihood of power outage occurrences and its social cost in four sectors.

Data about the time, location, size and cause of power outage during 1992 to 2009 in the eastern provinces of Canada were collected through system disturbances reports provided by NERC. For data collection, toward each day of power outage, the weather conditions for the same day were collected for all the years between 1992 and 2009. Since there were 38 days of power outage caused by weather circumstances in this area, information for 646 days were gathered (38 days × 17 years). Checking and removing missing data reduce the final number of days to 614, and for each day, seven values of input variables were collected. Data collection consist two sections: dataset I) extreme values for all the weather variables; dataset II) extreme value for wind speed and other weather factors at the same time as the maximum wind speed happened. Social costs of electric power outages in four sectors of residential, commercial, industrial and agriculture in Canada were collected from customer surveys in 1995. The surveys show the cost of each KWh of electric power failure per minutes. The costs were then updated to the present electric consumption price in 2015.

The proposed methodology was further verified through the training of ANN models with data collected for eastern Canadian provinces: Quebec, Ontario, New Brunswick and Nova Scotia. The data set, which included 614 data points, was partitioned into two sets of 512, i.e. 85% of the total, and 92, i.e. 15% of the total, data points for the training and validation/testing, respectively. The model performance in terms of testing RMSE, MAE and R^2 through testing data were compared. Results comparison shows that dataset I in all models provided better results. In addition the trained PNN model reached more accurate results than BPNN and GRNN. The accuracy of the PNN is checked by considering error thresholds and examining the predicted and actual outputs. The results showed that accepting a 4 percent risk of error in estimation, the model provides reliable predictions in 52.17% of the cases.

In the next step, the best model (e.g. PNN) and best dataset (e.g. Phase I) were chosen to develop a new model only for Quebec province. The results of the PNN model for Quebec, provided more accurate model. It can be concluded that, once dataset get more specific for one region, model can be trained in a better way. Once the likelihood of power failure is calculated, by identifying the average duration of power outage and the average cost for power failure per time, an estimation for social cost in different sector can be prepared. As a result, the social cost of electric power outage in one week in January and July 2015 in Quebec were estimated. The results showed that, in the case of electric power outage for one week in January 2015, the social cost would be \$/KWh 57,249.55 and for one week in June 2015 the social cost would be \$/KWh 92,751.71 in Quebec.

The present research helps electrical companies to more effectively predict the likelihood of electric power outage based on weather forecasting data. Furthermore, they are able to estimate the social cost of electric power failure in advance. This will provide useful information for further actions in risk mitigation, and will aide professionalisms in the process of creating choices to improve opportunities and to lessen threats.

6.2 RESEARCH CONTRIBUTIONS

The contributions of the present research are:

1) This research provide a model which is able to predict the probability of power outage based on the weather forecasting data. The developed model by predicting and warning about the possible power outage, is able to increase the safety of people's lives (e.g. provide enough power for emergency centers such as hospitals, or residential and commercial building), and reduce the social cost of power outage by being prepared for the power outage incident;

2) The present research helps electrical companies to estimate the social cost of electric power failure in different sectors; (i.e. residential, commercial, industrial and agriculture). This will provide useful information for further actions in risk mitigation, and will aide professionalisms in making decisions to improve opportunities and to lessen threats;

3) The proposed model is specifically developed for eastern Canada, since the weather condition especially in winter is more critical in Canada;

4) The proposed model consider all the main weather factors (e.g. temperature, wind speed, precipitation, humidity and lightning) in one model. It also identify the most critical and

effective weather variable on the power grids;

5) This research considered both big blackouts and small power outages in big period of time (eighteen years) to provide more reliable model that can be used by electric companies to predict the daily power outage.

6.3 RESEARCH LIMITATION

The developed framework has the following limitations:

1) Since there is no enough information about the duration of electric power outage, the proposed model can only predict the likelihood of power failure occurrences and does not predict the duration of upcoming power outage. Furthermore the model is not able to predict the hour of likely electric power outage occurrence;
2) Data provided by system disturbances reports do not give information about the specific location of power outage, and only considers the location in provincial scale. As a result the ANN models are not localized in details;
3) Since the model is constituted from several independent ANNs, more historical data points to feed each network can provide a better sense about the weather condition in years and provide more accurate results;
4) The model is limited to average social cost of the power outages. To forecast the changes of the social costs from 1995 to 2015, only the future value of the money is calculated. However, in reality the technology and manufacturing have significantly changed during this period, and changes in electricity consumption pattern should be considered.

6.4 FUTURE WORKS

The present research can be further enhanced through the following steps:

1) Weather data can be collected in more details for a specific city, which make the model to be trained with more detailed factors, and could be useful in the following categories:

    a) A future work can concentrate on finding the areas in the cities that provide more consequences in case of power outage. For example, nonfunctional traffic light in street main streets could cause traffic jam which does not allow the emergency vehicles pass to their duties.

    b) Geographical and climate situation of a specific city could provide more detailed variables about the electric consumption patterns that can be considered in training the models. For example, the popular places (e.g. hospitals, stadium, restaurants, and etc.) consume more electric power and absorbs higher number of people in that area. As a result, in case of power outage, the social cost for these kind of place would be higher, and the property of these places could be categorized.

    c) Based on the cultural, economic, climatic features of the city, electrical companies are able to increase their ability in preventing the power outage by knowing the critical points of their territories, as well as the climatic information.

2) Local forecasted weather information could be used to predict the risk of the likely electric power outages in local areas. These information can also be implemented using the GIS maps to identify the risk assessment of that area. As a result, risk mitigation

could be applied and forehand schedule be utilized to optimizes the consequences.

3) Inspection tools such as infrared thermographic camera can be used to check the electrical equipment and determine their critical points in case of abnormal weather condition. This information can be compounded with proposed model to provide a more comprehensive accurate forecasting system.
4) The future work can consider the direct costs of electric power outage for electrical companies based on the proposed model and compare the results with the social cost. As a results. There will be a better estimation of lost cost and it is expected to propose more accurate mitigation plan for budgets.

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APPENDIX I

DATASET I – Train Data

Provinces	Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity %	Lightning	Actual Output
Quebec	4-Nov-95	0.8713	305600	31	-1.7	0.000049	100	0	0
	4-Nov-96	0.8713	305600	56	-3.4	0.000056	72	0	0
	4-Nov-97	0.8713	305600	31	4.6	0.000222	100	0	0
	4-Nov-98	0.8713	305600	31	1.8	0.000173	99	0	0
	4-Nov-99	0.8713	305600	54	2.1	0.000204	97	0	0
	4-Nov-00	0.8713	305600	31	1.4	0.000157	100	0	0
	4-Nov-01	0.8713	305600	31	3.6	0.000143	97	0	0
	4-Nov-02	0.8713	305600	31	-8.3	0.000000	92	0	0
	4-Nov-03	0.8713	305600	57	-3.8	0.000000	67	0	0
	4-Nov-04	0.8713	305600	48	-4.3	0.000000	85	0	0
	4-Nov-06	0.8713	305600	31	-5.4	0.000000	90	0	0
	4-Nov-08	0.8713	305600	31	-1.3	0.000000	89	0	0
	4-Nov-09	0.8713	305600	44	-3.9	0.000000	88	0	0
Nova Scotia	14-Nov-04	0.8713	31800	48	-0.1	0.000261	100	0	1
	14-Nov-92	0.8713	31800	43	0.7	0.000094	97	0	0
	14-Nov-93	0.8713	31800	20	1.7	0.000356	97	0	0
	14-Nov-94	0.8713	31800	31	1.4	0.000000	91	0	0
	14-Nov-96	0.8713	31800	35	-2.2	0.000000	77	0	0
	14-Nov-97	0.8713	31800	43	3.9	0.000262	100	0	0
	14-Nov-98	0.8713	31800	31	1.8	0.000000	85	0	0
	14-Nov-99	0.8713	31800	57	5.5	0.000000	92	0	0
	14-Nov-00	0.8713	31800	31	5.9	0.000004	100	0	0
	14-Nov-01	0.8713	31800	31	-6.4	0.000044	92	0	0
	14-Nov-02	0.8713	31800	44	2.2	0.000619	100	0	0
	14-Nov-03	0.8713	31800	56	-1.8	0.000021	92	0	0
	14-Nov-05	0.8713	31800	32	4.5	0.000000	100	0	0
	14-Nov-07	0.8713	31800	31	-0.8	0.000000	96	0	0
	14-Nov-08	0.8713	31800	48	0.7	0.000326	97	0	0
	14-Nov-09	0.8713	31800	33	1.1	0.000000	100	0	0
Quebec	6-Jun-05	0.7362	305600	33	17	0.000120	87	0	1
	6-Jun-92	0.7362	305600	37	22	0.000100	95	1	0
	6-Jun-93	0.7362	305600	32	21.5	0.000000	99	0	0
	6-Jun-94	0.7362	305600	48	27	0.000407	87	1	0
	6-Jun-95	0.7362	305600	46	19.4	0.000315	93	1	0
	6-Jun-96	0.7362	305600	43	23.9	0.000000	81	0	0
	6-Jun-97	0.7362	305600	31	14.2	0.000000	95	0	0
	6-Jun-98	0.7362	305600	31	13.7	0.000000	98	0	0
	6-Jun-01	0.7362	305600	31	13.4	0.000067	100	0	0
	6-Jun-02	0.7362	305600	35	16.4	0.000000	94	0	0
	6-Jun-03	0.7362	305600	48	17.9	0.000230	95	1	0
	6-Jun-04	0.7362	305600	41	22.5	0.000000	79	0	0
	6-Jun-06	0.7362	305600	31	20	0.000000	89	0	0
	6-Jun-07	0.7362	305600	31	24.8	0.000000	98	0	0

New Brunswick	7-Jun-92	0.7362	31550	31	24.3	0.000346	92	1	0
	7-Jun-94	0.7362	31550	48	16.7	0.000341	100	0	0
	7-Jun-95	0.7362	31550	37	18.5	0.000000	91	0	0
	7-Jun-96	0.7362	31550	43	24.8	0.000278	95	1	0
	7-Jun-97	0.7362	31550	35	16	0.000000	97	0	0
	7-Jun-98	0.7362	31550	44	14.6	0.000000	99	0	0
	7-Jun-99	0.7362	31550	44	28.2	0.000000	91	0	0
	7-Jun-00	0.7362	31550	57	7.4	0.000292	99	0	0
	7-Jun-01	0.7362	31550	31	19	0.000806	100	1	0
	7-Jun-03	0.7362	31550	31	23.6	0.000000	99	0	0
	7-Jun-04	0.7362	31550	31	14.9	0.000213	94	0	0
	7-Jun-06	0.7362	31550	39	23.3	0.000024	100	1	0
	7-Jun-07	0.7362	31550	32	19.2	0.000083	92	1	0
	7-Jun-08	0.7362	31550	41	22.2	0.000000	91	0	0
	7-Jun-09	0.7362	31550	46	26.5	0.000000	100	0	0
Quebec	19-Jul-05	0.7854	305600	31	33.5	0.000000	94	0	1
	19-Jul-92	0.7854	305600	31	22.8	0.000000	97	0	0
	19-Jul-93	0.7854	305600	33	19.2	0.000000	90	0	0
	19-Jul-94	0.7854	305600	31	23.4	0.000111	96	1	0
	19-Jul-96	0.7854	305600	46	16.3	0.001236	92	0	0
	19-Jul-97	0.7854	305600	39	19.3	0.000000	100	0	0
	19-Jul-98	0.7854	305600	50	26.3	0.000000	91	0	0
	19-Jul-99	0.7854	305600	52	25.8	0.001083	97	1	0
	19-Jul-00	0.7854	305600	39	24.2	0.000380	100	1	0
	19-Jul-01	0.7854	305600	31	28.9	0.000000	92	0	0
	19-Jul-03	0.7854	305600	31	23.9	0.000593	97	1	0
	19-Jul-04	0.7854	305600	31	18.9	0.000078	97	1	0
	19-Jul-06	0.7854	305600	31	25.7	0.000000	95	0	0
	19-Jul-07	0.7854	305600	31	23.7	0.000157	96	1	0
Quebec	1-Aug-93	0.7761	305600	31	25.4	0.000000	100	0	0
	1-Aug-94	0.7761	305600	32	29.1	0.000000	100	0	0
	1-Aug-95	0.7761	305600	31	31.5	0.001074	97	1	0
	1-Aug-96	0.7761	305600	31	23.5	0.000078	84	1	0
	1-Aug-97	0.7761	305600	56	27.1	0.000111	100	1	0
	1-Aug-98	0.7761	305600	31	23.6	0.000000	100	0	0
	1-Aug-00	0.7761	305600	31	28.7	0.000000	97	0	0
	1-Aug-01	0.7761	305600	31	28.4	0.000000	91	0	0
	1-Aug-03	0.7761	305600	31	27.8	0.000000	97	0	0
	1-Aug-04	0.7761	305600	80	29.5	0.001204	94	1	0
	1-Aug-06	0.7761	305600	33	22.6	0.000000	97	0	0
	1-Aug-07	0.7761	305600	31	23.5	0.000000	93	0	0
	1-Aug-08	0.7761	305600	39	18.8	0.000306	91	1	0
	1-Aug-09	0.7761	305600	31	27.1	0.000000	86	0	0
Quebec	9-Aug-05	0.7761	305600	52	34.1	0.000000	96	0	1
	9-Aug-92	0.7761	305600	37	28.4	0.000000	99	0	0
	9-Aug-94	0.7761	305600	31	23.9	0.000000	97	0	0
	9-Aug-95	0.7761	305600	31	33.1	0.000000	95	0	0
	9-Aug-96	0.7761	305600	31	28	0.000067	81	1	0
	9-Aug-97	0.7761	305600	31	29.1	0.000000	100	0	0
	9-Aug-98	0.7761	305600	31	32.9	0.000000	100	0	0
	9-Aug-99	0.7761	305600	39	17.8	0.000155	98	1	0

	9-Aug-00	0.7761	305600	31	18.7	0.000290	97	1	0
	9-Aug-02	0.7761	305600	32	22.2	0.000000	85	0	0
	9-Aug-03	0.7761	305600	31	19.3	0.000111	97	1	0
	9-Aug-04	0.7761	305600	31	19.8	0.001667	95	1	0
	9-Aug-06	0.7761	305600	31	23.7	0.000000	91	0	0
	9-Aug-07	0.7761	305600	52	21	0.000340	100	1	0
	9-Aug-09	0.7761	305600	31	25.1	0.000000	90	0	0
Ontario	3-Feb-92	0.8975	152000	31	-13.6	0.000000	91	0	0
	3-Feb-94	0.8975	152000	50	-20	0.000062	91	0	0
	3-Feb-95	0.8975	152000	31	-19.6	0.000000	70	0	0
	3-Feb-96	0.8975	152000	31	-29.1	0.000000	62	0	0
	3-Feb-97	0.8975	152000	31	-11.2	0.000048	100	0	0
	3-Feb-98	0.8975	152000	31	-16.3	0.000014	83	0	0
	3-Feb-99	0.8975	152000	44	-3.5	0.000000	100	0	0
	3-Feb-01	0.8975	152000	37	-11.1	0.000144	100	0	0
	3-Feb-05	0.8975	152000	19	-6.6	0.000000	97	0	0
	3-Feb-06	0.8975	152000	31	-0.7	0.000069	99	0	0
	3-Feb-08	0.8975	152000	31	-8	0.000023	94	0	0
	3-Feb-09	0.8975	152000	33	-22.3	0.000011	78	0	0
Quebec	10-Aug-92	0.7761	305600	31	25.6	0.000000	88	0	0
	10-Aug-93	0.7761	305600	31	24.9	0.001019	100	1	0
	10-Aug-94	0.7761	305600	31	22.6	0.000000	97	0	0
	10-Aug-95	0.7761	305600	31	28.7	0.000000	97	0	0
	10-Aug-96	0.7761	305600	31	26.6	0.000000	81	0	0
	10-Aug-97	0.7761	305600	31	21.2	0.000000	100	0	0
	10-Aug-98	0.7761	305600	31	33.4	0.000000	87	0	0
	10-Aug-99	0.7761	305600	41	19.9	0.000000	76	0	0
	10-Aug-00	0.7761	305600	31	16.7	0.000396	98	0	0
	10-Aug-02	0.7761	305600	32	23.3	0.000000	93	0	0
	10-Aug-05	0.7761	305600	31	25.9	0.000130	94	1	0
	10-Aug-07	0.7761	305600	31	26.7	0.000000	90	0	0
	10-Aug-08	0.7761	305600	31	19.3	0.000000	91	0	0
	10-Aug-09	0.7761	305600	31	19.6	0.000183	98	1	0
Quebec	26-Aug-03	0.7761	305600	31	19.6	0.000000	91	0	0
	26-Aug-92	0.7761	305600	31	17	0.000500	94	0	0
	26-Aug-94	0.7761	305600	31	24.4	0.000000	95	0	0
	26-Aug-95	0.7761	305600	31	15.3	0.000000	91	0	0
	26-Aug-96	0.7761	305600	46	20.2	0.000000	68	0	0
	26-Aug-97	0.7761	305600	31	18.6	0.000389	100	1	0
	26-Aug-98	0.7761	305600	31	15.3	0.000142	100	0	0
	26-Aug-99	0.7761	305600	31	25.7	0.000000	95	0	0
	26-Aug-02	0.7761	305600	31	23.4	0.000155	96	1	0
	26-Aug-04	0.7761	305600	31	25.5	0.000000	99	0	0
	26-Aug-05	0.7761	305600	37	27.1	0.000000	90	0	0
	26-Aug-06	0.7761	305600	31	17.4	0.000000	98	0	0
	26-Aug-08	0.7761	305600	31	20.5	0.000000	77	0	0
	26-Aug-09	0.7761	305600	56	26.6	0.000000	81	0	0
New Brunswick	28-Sep-93	0.7226	31550	20	21.3	0.000583	95	1	0
	28-Sep-94	0.7226	31550	50	17.5	0.000364	100	1	0
	28-Sep-96	0.7226	31550	43	15.8	0.000000	89	0	0

	28-Sep-97	0.7226	31550	41	16.2	0.000000	93	0	0
	28-Sep-98	0.7226	31550	31	21.3	0.000910	98	1	0
	28-Sep-99	0.7226	31550	31	20.9	0.000000	84	0	0
	28-Sep-05	0.7226	31550	19	5.7	0.000000	99	0	0
	28-Sep-07	0.7226	31550	39	24.8	0.000000	99	0	0
	28-Sep-08	0.7226	31550	91	20.9	0.001377	95	1	0
	28-Sep-09	0.7226	31550	70	19.5	0.000907	99	1	0
Quebec	26-Dec-03	0.9583	305600	31	-2	0.000256	98	0	1
	26-Dec-93	0.9583	305600	44	-7.6	0.000171	94	0	0
	26-Dec-94	0.9583	305600	56	-6.1	0.000014	75	0	0
	26-Dec-95	0.9583	305600	31	0.7	0.000074	100	0	0
	26-Dec-96	0.9583	305600	37	-16.6	0.000000	76	0	0
	26-Dec-97	0.9583	305600	31	-0.7	0.000065	100	0	0
	26-Dec-98	0.9583	305600	31	-22.7	0.000000	77	0	0
	26-Dec-99	0.9583	305600	31	-11.7	0.000000	86	0	0
	26-Dec-00	0.9583	305600	41	-13.4	0.000038	91	0	0
	26-Dec-02	0.9583	305600	50	-7.1	0.000017	85	0	0
	26-Dec-05	0.9583	305600	41	-7.9	0.000271	93	0	0
	26-Dec-06	0.9583	305600	31	-6.4	0.000050	88	0	0
	26-Dec-07	0.9583	305600	35	-9.3	0.000000	86	0	0
	26-Dec-08	0.9583	305600	31	-22.8	0.000000	75	0	0
Ontario	9-Mar-02	0.8860	152000	89	-4.3	0.000125	93	0	1
	9-Mar-92	0.8860	152000	52	-5.8	0.000074	100	0	0
	9-Mar-94	0.8860	152000	35	-10.9	0.000000	75	0	0
	9-Mar-95	0.8860	152000	31	-14.4	0.000000	85	0	0
	9-Mar-96	0.8860	152000	31	-23.6	0.000000	69	0	0
	9-Mar-97	0.8860	152000	41	-20.3	0.000000	69	0	0
	9-Mar-99	0.8860	152000	39	-10.4	0.000000	50	0	0
	9-Mar-01	0.8860	152000	31	-9.4	0.000028	85	0	0
	9-Mar-06	0.8860	152000	37	-1.6	0.000098	100	0	0
	9-Mar-07	0.8860	152000	35	-16	0.000000	63	0	0
	9-Mar-08	0.8860	152000	52	-18.1	0.000056	73	0	0
	9-Mar-09	0.8860	152000	39	-9.4	0.000204	83	0	0
Quebec	2-Aug-02	0.7761	305600	31	22.4	0.000250	97	1	1
	2-Aug-92	0.7761	305600	41	21.1	0.000074	95	1	0
	2-Aug-93	0.7761	305600	31	25.2	0.000000	100	0	0
	2-Aug-95	0.7761	305600	31	21.4	0.000130	97	1	0
	2-Aug-98	0.7761	305600	46	27.8	0.000102	97	1	0
	2-Aug-99	0.7761	305600	31	23.8	0.000000	96	0	0
	2-Aug-00	0.7761	305600	33	24.8	0.000178	95	1	0
	2-Aug-01	0.7761	305600	32	31	0.000000	84	0	0
	2-Aug-03	0.7761	305600	31	25.8	0.000000	96	0	0
	2-Aug-04	0.7761	305600	35	26.2	0.000000	94	0	0
	2-Aug-05	0.7761	305600	31	19	0.000000	97	0	0
	2-Aug-06	0.7761	305600	37	27.4	0.000000	86	0	0
	2-Aug-07	0.7761	305600	31	19.8	0.000486	96	1	0
	2-Aug-08	0.7761	305600	33	17.3	0.000083	90	1	0
Quebec	14-Aug-92	0.7761	305600	31	20.1	0.000000	97	0	0
	14-Aug-93	0.7761	305600	31	21.3	0.000014	100	1	0
	14-Aug-94	0.7761	305600	50	23.9	0.000111	91	1	0
	14-Aug-95	0.7761	305600	31	19.9	0.000000	100	0	0

	14-Aug-96	0.7761	305600	31	23.6	0.000000	80	0	0
	14-Aug-97	0.7761	305600	31	15.9	0.000049	100	0	0
	14-Aug-99	0.7761	305600	37	22.7	0.000382	98	1	0
	14-Aug-00	0.7761	305600	31	24.4	0.000000	99	0	0
	14-Aug-01	0.7761	305600	69	25	0.000000	99	0	0
	14-Aug-03	0.7761	305600	37	24.1	0.000000	79	0	0
	14-Aug-04	0.7761	305600	31	25.6	0.000167	93	1	0
	14-Aug-05	0.7761	305600	31	22.6	0.000000	84	0	0
	14-Aug-06	0.7761	305600	33	23.9	0.000056	87	1	0
	14-Aug-07	0.7761	305600	31	19.7	0.000000	95	0	0
	14-Aug-09	0.7761	305600	31	30.8	0.000056	94	1	0
Quebec	8-Sep-02	0.7226	305600	33	7.7	0.000419	96	0	1
	8-Sep-92	0.7226	305600	31	21.5	0.000111	94	1	0
	8-Sep-93	0.7226	305600	31	20.9	0.000000	100	0	0
	8-Sep-94	0.7226	305600	31	20.3	0.000028	100	1	0
	8-Sep-95	0.7226	305600	37	22.7	0.000101	96	1	0
	8-Sep-96	0.7226	305600	31	21.4	0.000000	79	0	0
	8-Sep-97	0.7226	305600	31	20	0.000000	100	0	0
	8-Sep-98	0.7226	305600	31	15.8	0.000063	97	0	0
	8-Sep-00	0.7226	305600	44	7.7	0.000000	95	0	0
	8-Sep-01	0.7226	305600	31	12.2	0.000000	97	0	0
	8-Sep-03	0.7226	305600	33	6	0.000000	82	0	0
	8-Sep-05	0.7226	305600	31	25.6	0.000000	83	0	0
	8-Sep-06	0.7226	305600	33	25.6	0.000000	99	0	0
	8-Sep-08	0.7226	305600	31	19.7	0.000201	100	1	0
	8-Sep-09	0.7226	305600	31	20	0.000000	95	0	0
Ontario	9-Sep-93	0.7226	152000	59	15.5	0.000421	97	0	0
	9-Sep-94	0.7226	152000	43	13.4	0.000333	97	0	0
	9-Sep-95	0.7226	152000	46	14	0.000278	85	0	0
	9-Sep-97	0.7226	152000	31	21.1	0.000000	92	0	0
	9-Sep-08	0.7226	152000	37	13.8	0.000000	93	0	0
	9-Sep-99	0.7226	152000	39	23.3	0.000000	93	0	0
	9-Sep-00	0.7226	152000	31	23.6	0.000000	90	0	0
	9-Sep-01	0.7226	152000	46	26.5	0.000222	100	1	0
	9-Sep-03	0.7226	152000	31	20.8	0.000000	84	0	0
	9-Sep-04	0.7226	152000	31	15	0.000028	94	0	0
	9-Sep-05	0.7226	152000	31	19	0.000000	86	0	0
	9-Sep-06	0.7226	152000	35	13.1	0.000000	99	0	0
	9-Sep-07	0.7226	152000	33	20.4	0.000019	91	1	0
	9-Sep-08	0.7226	152000	33	15.4	0.000381	98	0	0
	9-Sep-09	0.7226	152000	31	23.8	0.000000	84	0	0
Quebec	7-Nov-02	0.8713	305600	52	-6.9	0.000042	90	0	1
	7-Nov-92	0.8713	305600	30	-10.8	0.000006	87	0	0
	7-Nov-95	0.8713	305600	50	-5.8	0.000611	96	0	0
	7-Nov-96	0.8713	305600	41	-6.8	0.000144	73	0	0
	7-Nov-97	0.8713	305600	31	-6.8	0.000000	100	0	0
	7-Nov-98	0.8713	305600	31	-2.4	0.000000	90	0	0
	7-Nov-99	0.8713	305600	31	-1.6	0.000000	89	0	0
	7-Nov-00	0.8713	305600	31	4.8	0.000017	99	0	0
	7-Nov-03	0.8713	305600	31	-6.6	0.000000	92	0	0
	7-Nov-04	0.8713	305600	31	-2.4	0.000048	95	0	0

	7-Nov-05	0.8713	305600	54	2.6	0.000296	97	0	0
	7-Nov-06	0.8713	305600	35	-8.6	0.000000	92	0	0
	7-Nov-07	0.8713	305600	56	-2.5	0.000575	95	0	0
	7-Nov-08	0.8713	305600	31	2	0.000130	97	0	0
Quebec	11-Jun-92	0.7362	305600	31	18.4	0.000000	93	0	0
	11-Jun-93	0.7362	305600	31	16	0.000000	97	0	0
	11-Jun-94	0.7362	305600	54	29	0.000000	97	0	0
	11-Jun-95	0.7362	305600	31	13.9	0.000222	95	0	0
	11-Jun-96	0.7362	305600	41	27.2	0.000000	82	0	0
	11-Jun-97	0.7362	305600	37	19.7	0.000000	81	0	0
	11-Jun-98	0.7362	305600	31	27.2	0.000000	98	0	0
	11-Jun-99	0.7362	305600	31	27.1	0.000000	93	0	0
	11-Jun-02	0.7362	305600	31	15.6	0.001167	97	0	0
	11-Jun-03	0.7362	305600	35	21.1	0.000292	98	1	0
	11-Jun-04	0.7362	305600	52	14.8	0.000000	64	0	0
	11-Jun-05	0.7362	305600	31	21.8	0.000000	83	0	0
	11-Jun-06	0.7362	305600	31	15.2	0.000395	98	0	0
	11-Jun-07	0.7362	305600	31	24.5	0.000000	100	0	0
	21-Jul-01	0.7854	305600	31	33.5	0.000022	94	1	1
	21-Jul-92	0.7854	305600	37	24.2	0.000250	90	1	0
Quebec	21-Jul-94	0.7854	305600	41	29.8	0.000630	95	1	0
	21-Jul-96	0.7854	305600	31	18.2	0.000423	85	1	0
	21-Jul-97	0.7854	305600	32	18.3	0.000028	84	1	0
	21-Jul-98	0.7854	305600	31	25.2	0.000000	97	0	0
	21-Jul-99	0.7854	305600	32	26.6	0.000000	81	0	0
	21-Jul-00	0.7854	305600	31	19.2	0.000167	94	1	0
	21-Jul-02	0.7854	305600	41	28.3	0.000000	89	0	0
	21-Jul-03	0.7854	305600	31	21.5	0.000071	97	1	0
	21-Jul-05	0.7854	305600	31	28.4	0.000000	89	0	0
	21-Jul-06	0.7854	305600	31	24.5	0.000056	96	1	0
	21-Jul-07	0.7854	305600	31	22.8	0.000074	93	1	0
	21-Jul-08	0.7854	305600	31	20.5	0.000306	91	1	0
	21-Jul-09	0.7854	305600	35	25.1	0.000000	96	0	0
Quebec	22-Jul-01	0.7854	305600	31	20	0.000028	97	1	1
	22-Jul-92	0.7854	305600	31	19.4	0.000000	96	0	0
	22-Jul-93	0.7854	305600	31	17.6	0.000333	100	1	0
	22-Jul-95	0.7854	305600	35	24.1	0.000000	100	0	0
	22-Jul-96	0.7854	305600	33	17.1	0.000000	82	0	0
	22-Jul-97	0.7854	305600	31	17.6	0.000000	89	0	0
	22-Jul-98	0.7854	305600	46	27.5	0.000689	100	1	0
	22-Jul-99	0.7854	305600	31	26.1	0.000167	99	1	0
	22-Jul-00	0.7854	305600	31	22.9	0.000296	98	1	0
	22-Jul-02	0.7854	305600	44	31.4	0.000056	89	1	0
	22-Jul-03	0.7854	305600	31	18.6	0.000194	95	1	0
	22-Jul-04	0.7854	305600	39	29.4	0.000000	96	0	0
	22-Jul-05	0.7854	305600	31	27.1	0.000278	96	1	0
	22-Jul-06	0.7854	305600	31	26.7	0.000000	97	0	0
	22-Jul-07	0.7854	305600	31	25.2	0.000000	93	0	0
	22-Jul-08	0.7854	305600	31	22.8	0.000100	91	1	0
	22-Jul-09	0.7854	305600	31	18.2	0.000154	98	1	0
Quebec	24-Jul-01	0.7854	305600	41	30.4	0.000375	97	1	1

	24-Jul-92	0.7854	305600	31	26.4	0.000000	100	0	0
	24-Jul-93	0.7854	305600	31	14.7	0.000063	94	0	0
	24-Jul-94	0.7854	305600	31	28.5	0.000896	100	1	0
	24-Jul-95	0.7854	305600	31	26	0.001117	100	1	0
	24-Jul-96	0.7854	305600	31	24.8	0.000000	83	0	0
	24-Jul-97	0.7854	305600	35	28.8	0.000000	100	0	0
	24-Jul-98	0.7854	305600	31	24.9	0.000046	97	1	0
	24-Jul-99	0.7854	305600	37	23.9	0.000000	98	0	0
	24-Jul-00	0.7854	305600	31	20.7	0.000000	100	0	0
	24-Jul-02	0.7854	305600	31	20.7	0.000000	93	0	0
	24-Jul-04	0.7854	305600	32	21.4	0.000587	92	1	0
	24-Jul-05	0.7854	305600	44	22.8	0.000000	72	0	0
	24-Jul-06	0.7854	305600	31	23.8	0.000000	97	0	0
	24-Jul-07	0.7854	305600	32	30.8	0.000000	96	0	0
	24-Jul-08	0.7854	305600	31	21.7	0.000000	90	0	0
	24-Jul-09	0.7854	305600	31	26.7	0.000000	98	0	0
Quebec	10-Jul-00	0.7854	305600	37	21.8	0.000354	100	1	1
	10-Jul-92	0.7854	305600	31	15.4	0.000187	99	0	0
	10-Jul-93	0.7854	305600	31	21.8	0.000204	97	1	0
	10-Jul-94	0.7854	305600	31	26.4	0.000694	89	1	0
	10-Jul-95	0.7854	305600	31	24.7	0.000000	97	0	0
	10-Jul-96	0.7854	305600	31	23.1	0.000574	89	1	0
	10-Jul-98	0.7854	305600	31	16.2	0.000319	100	0	0
	10-Jul-99	0.7854	305600	31	19.1	0.000022	96	1	0
	10-Jul-01	0.7854	305600	31	20.9	0.000024	97	1	0
	10-Jul-02	0.7854	305600	35	20.7	0.000000	85	0	0
	10-Jul-03	0.7854	305600	48	24.5	0.000000	64	0	0
	10-Jul-05	0.7854	305600	31	23.8	0.000000	92	0	0
	10-Jul-06	0.7854	305600	31	19.1	0.000032	96	1	0
	10-Jul-07	0.7854	305600	31	16.8	0.000128	97	0	0
	10-Jul-08	0.7854	305600	31	24.7	0.000685	93	1	0
	10-Jul-09	0.7854	305600	31	26.9	0.000000	93	0	0
Ontario	13-Jul-00	0.7854	152000	31	22.7	0.000472	78	1	1
	13-Jul-92	0.7854	152000	31	18.4	0.000000	100	0	0
	13-Jul-94	0.7854	152000	31	20.8	0.000000	88	0	0
	13-Jul-95	0.7854	152000	31	30.4	0.000028	82	1	0
	13-Jul-96	0.7854	152000	33	25.1	0.000083	83	1	0
	13-Jul-97	0.7854	152000	44	28.2	0.000000	89	0	0
	13-Jul-98	0.7854	152000	44	28	0.000028	88	1	0
	13-Jul-99	0.7854	152000	33	25.8	0.000000	90	0	0
	13-Jul-01	0.7854	152000	32	19.3	0.000000	96	0	0
	13-Jul-02	0.7854	152000	31	24.7	0.000000	88	0	0
	13-Jul-03	0.7854	152000	31	26.8	0.000000	91	0	0
	13-Jul-04	0.7854	152000	31	27	0.000000	95	0	0
	13-Jul-05	0.7854	152000	33	34	0.000000	91	0	0
	13-Jul-07	0.7854	152000	31	19.8	0.000444	98	1	0
	13-Jul-08	0.7854	152000	54	23	0.000000	97	0	0
	13-Jul-09	0.7854	152000	32	14.6	0.000042	91	0	0
Quebec	17-Jul-00	0.7854	305600	31	17.1	0.000444	100	1	1
	17-Jul-92	0.7854	305600	32	20.3	0.000000	89	0	0
	17-Jul-93	0.7854	305600	37	11.8	0.000116	95	0	0

	17-Jul-94	0.7854	305600	31	20.8	0.000000	99	0	0
	17-Jul-95	0.7854	305600	31	18.5	0.000000	97	0	0
	17-Jul-97	0.7854	305600	41	24.6	0.000528	100	1	0
	17-Jul-98	0.7854	305600	32	24.2	0.000630	100	1	0
	17-Jul-01	0.7854	305600	31	22.2	0.000000	100	0	0
	17-Jul-02	0.7854	305600	33	26.5	0.000000	100	0	0
	17-Jul-03	0.7854	305600	31	27.1	0.000000	94	0	0
	17-Jul-04	0.7854	305600	33	24.1	0.000000	95	0	0
	17-Jul-05	0.7854	305600	31	27.8	0.000000	95	0	0
	17-Jul-06	0.7854	305600	31	25.5	0.000306	100	1	0
	17-Jul-09	0.7854	305600	31	19.4	0.000167	100	1	0
Ontario	22-Aug-00	0.7761	152000	31	19.6	0.000167	92	1	1
	22-Aug-92	0.7761	152000	31	24.4	0.000000	91	0	0
	22-Aug-93	0.7761	152000	31	24	0.000000	99	0	0
	22-Aug-94	0.7761	152000	31	19.4	0.000000	93	0	0
	22-Aug-95	0.7761	152000	31	19.2	0.000000	77	0	0
	22-Aug-97	0.7761	152000	37	14.5	0.000136	97	0	0
	22-Aug-98	0.7761	152000	31	23.5	0.000000	98	0	0
	22-Aug-99	0.7761	152000	31	25.5	0.000000	87	0	0
	22-Aug-02	0.7761	152000	31	21.8	0.000444	97	1	0
	22-Aug-03	0.7761	152000	51	19.5	0.000000	75	0	0
	22-Aug-04	0.7761	152000	50	19.5	0.001417	96	1	0
	22-Aug-05	0.7761	152000	31	16.7	0.000444	100	0	0
	22-Aug-06	0.7761	152000	31	20.6	0.000167	100	1	0
	22-Aug-07	0.7761	152000	31	19.8	0.000000	91	0	0
	22-Aug-08	0.7761	152000	31	29.3	0.000000	80	0	0
	22-Aug-09	0.7761	152000	37	20.2	0.000000	97	0	0
New Brunswick	20-Dec-00	0.9583	31550	98	-7.1	0.000335	100	0	1
	20-Dec-97	0.9583	31550	37	-14.4	0.000000	91	0	0
	20-Dec-98	0.9583	31550	52	-14.4	0.000011	96	0	0
	20-Dec-01	0.9583	31550	31	-7.4	0.000000	89	0	0
	20-Dec-02	0.9583	31550	48	-2	0.000093	96	0	0
	20-Dec-03	0.9583	31550	31	-12.2	0.000000	87	0	0
	20-Dec-04	0.9583	31550	31	-2	0.000049	100	0	0
	20-Dec-05	0.9583	31550	35	-10	0.000028	92	0	0
	20-Dec-06	0.9583	31550	31	-11.1	0.000000	77	0	0
	20-Dec-07	0.9583	31550	44	-12.9	0.000000	97	0	0
	20-Dec-08	0.9583	31550	33	-20.7	0.000012	79	0	0
	20-Dec-09	0.9583	31550	52	-9.3	0.000076	94	0	0
Ontario	11-Jan-99	1.0000	152000	32	-29.5	0.000100	75	0	1
	11-Jan-92	1.0000	152000	31	-22.6	0.000000	91	0	0
	11-Jan-93	1.0000	152000	31	-20.4	0.000000	64	0	0
	11-Jan-94	1.0000	152000	50	-17.8	0.000037	95	0	0
	11-Jan-95	1.0000	152000	37	-23.1	0.000079	76	0	0
	11-Jan-96	1.0000	152000	31	-21.2	0.000000	77	0	0
	11-Jan-97	1.0000	152000	31	-22.3	0.000016	97	0	0
	11-Jan-98	1.0000	152000	35	-18.1	0.000056	90	0	0
	11-Jan-01	1.0000	152000	31	-13.7	0.000000	91	0	0
	11-Jan-02	1.0000	152000	31	-3.8	0.000037	94	0	0
	11-Jan-03	1.0000	152000	33	-20	0.000012	73	0	0
	11-Jan-05	1.0000	152000	31	-21.5	0.000000	85	0	0

	11-Jan-06	1.0000	152000	31	-6.7	0.000222	100	0	0
	11-Jan-07	1.0000	152000	31	-13.6	0.000035	90	0	0
Ontario	4-Mar-92	0.8860	152000	31	-9.8	0.000000	92	0	0
	4-Mar-93	0.8860	152000	46	-11.2	0.000000	72	0	0
	4-Mar-94	0.8860	152000	37	-4.2	0.000000	85	0	0
	4-Mar-95	0.8860	152000	31	-10	0.000006	85	0	0
	4-Mar-96	0.8860	152000	56	-20.2	0.000167	72	0	0
	4-Mar-97	0.8860	152000	31	-9.2	0.000006	97	0	0
	4-Mar-98	0.8860	152000	31	-12.1	0.000000	92	0	0
	4-Mar-01	0.8860	152000	46	-10.8	0.000028	75	0	0
	4-Mar-02	0.8860	152000	37	-24.6	0.000000	65	0	0
	4-Mar-03	0.8860	152000	44	-20.9	0.000094	83	0	0
	4-Mar-04	0.8860	152000	31	-2	0.000047	100	0	0
	4-Mar-05	0.8860	152000	31	-13	0.000000	83	0	0
	4-Mar-06	0.8860	152000	52	-12.5	0.000000	81	0	0
	4-Mar-07	0.8860	152000	32	-13.2	0.000040	82	0	0
Quebec	6-Jan-98	1.0000	305600	31	-20	0.000028	80	0	1
	6-Jan-92	1.0000	305600	31	-1.2	0.000395	100	0	0
	6-Jan-93	1.0000	305600	31	-19.8	0.000000	91	0	0
	6-Jan-94	1.0000	305600	65	-18.5	0.000000	80	0	0
	6-Jan-95	1.0000	305600	41	-24.6	0.000000	71	0	0
	6-Jan-96	1.0000	305600	31	-24.1	0.000000	89	0	0
	6-Jan-97	1.0000	305600	31	-12.3	0.000014	84	0	0
	6-Jan-99	1.0000	305600	52	-20	0.000118	93	0	0
	6-Jan-00	1.0000	305600	31	-10.1	0.000000	88	0	0
	6-Jan-01	1.0000	305600	33	-6.5	0.000169	97	0	0
	6-Jan-02	1.0000	305600	31	-18.2	0.000028	91	0	0
	6-Jan-03	1.0000	305600	31	-17.6	0.000000	91	0	0
	6-Jan-04	1.0000	305600	31	-11	0.000056	87	0	0
	6-Jan-05	1.0000	305600	31	-23.5	0.000000	71	0	0
	6-Jan-06	1.0000	305600	31	-11.5	0.000035	100	0	0
	6-Jan-07	1.0000	305600	31	-1	0.000134	97	0	0
	6-Jan-08	1.0000	305600	39	-10.5	0.000083	92	0	0
	6-Jan-09	1.0000	305600	59	-14.3	0.000000	61	0	0
Ontario	8-Jan-92	1.0000	152000	32	-22.1	0.000000	80	0	0
	8-Jan-93	1.0000	152000	31	-20.4	0.000000	66	0	0
	8-Jan-94	1.0000	152000	33	-26	0.000000	69	0	0
	8-Jan-95	1.0000	152000	50	-20.8	0.000060	100	0	0
	8-Jan-96	1.0000	152000	31	-22.6	0.000056	85	0	0
	8-Jan-97	1.0000	152000	31	-20.2	0.000000	95	0	0
	8-Jan-99	1.0000	152000	31	-18.6	0.000028	90	0	0
	8-Jan-02	1.0000	152000	33	-9.4	0.000056	93	0	0
	8-Jan-03	1.0000	152000	37	-9.5	0.000092	95	0	0
	8-Jan-04	1.0000	152000	31	-29.2	0.000022	70	0	0
	8-Jan-05	1.0000	152000	31	-6.9	0.000003	95	0	0
	8-Jan-06	1.0000	152000	31	-10.2	0.000019	95	0	0
	8-Jan-07	1.0000	152000	41	-4	0.000156	91	0	0
	8-Jan-08	1.0000	152000	31	6	0.000368	100	0	0
	8-Jan-09	1.0000	152000	33	-19.7	0.000006	85	0	0
Ontario	25-Jun-98	0.7362	152000	37	26.7	0.000903	99	1	0
	25-Jun-92	0.7362	152000	31	22.6	0.000000	93	0	0

	25-Jun-94	0.7362	152000	54	18.5	0.000433	95	1	0
	25-Jun-95	0.7362	152000	31	27.9	0.000033	82	1	0
	25-Jun-96	0.7362	152000	44	20.4	0.000278	100	1	0
	25-Jun-97	0.7362	152000	56	25.7	0.000667	95	1	0
	25-Jun-99	0.7362	152000	37	27.8	0.000000	100	0	0
	25-Jun-02	0.7362	152000	31	27.7	0.000500	90	1	0
	25-Jun-03	0.7362	152000	31	31.7	0.000000	75	0	0
	25-Jun-04	0.7362	152000	39	17.7	0.000000	92	0	0
	25-Jun-05	0.7362	152000	31	26.9	0.000000	96	0	0
	25-Jun-06	0.7362	152000	31	25.7	0.000000	81	0	0
	25-Jun-07	0.7362	152000	39	27.5	0.001556	91	1	0
	25-Jun-08	0.7362	152000	46	24.7	0.000000	96	0	0
Quebec	4-Dec-97	0.9583	305600	37	0.9	0.000167	98	0	1
	4-Dec-92	0.9583	305600	46	-2.6	0.000038	89	0	0
	4-Dec-93	0.9583	305600	31	-4.2	0.000000	100	0	0
	4-Dec-95	0.9583	305600	31	-14.1	0.000048	100	0	0
	4-Dec-96	0.9583	305600	31	-2.2	0.000000	97	0	0
	4-Dec-98	0.9583	305600	41	-9	0.000125	96	0	0
	4-Dec-99	0.9583	305600	31	-9	0.000000	97	0	0
	4-Dec-00	0.9583	305600	31	-16.1	0.000000	99	0	0
	4-Dec-01	0.9583	305600	32	-10	0.000000	97	0	0
	4-Dec-02	0.9583	305600	50	-17.1	0.000000	81	0	0
	4-Dec-03	0.9583	305600	39	-6.8	0.000059	90	0	0
	4-Dec-04	0.9583	305600	61	-12.1	0.000458	99	0	0
	4-Dec-05	0.9583	305600	50	1.5	0.000538	97	0	0
	4-Dec-06	0.9583	305600	32	-4.3	0.000225	91	0	0
	4-Dec-07	0.9583	305600	50	-7.1	0.000000	77	0	0
Quebec	7-Dec-97	0.9583	305600	31	-1.3	0.000130	100	0	1
	7-Dec-93	0.9583	305600	31	-11.7	0.000038	94	0	0
	7-Dec-95	0.9583	305600	32	-19.7	0.000000	91	0	0
	7-Dec-96	0.9583	305600	31	-1.7	0.000003	93	0	0
	7-Dec-98	0.9583	305600	70	-3.4	0.000235	100	0	0
	7-Dec-99	0.9583	305600	31	-1.1	0.000141	95	0	0
	7-Dec-00	0.9583	305600	31	-15.1	0.000000	86	0	0
	7-Dec-02	0.9583	305600	41	-20.4	0.000000	82	0	0
	7-Dec-03	0.9583	305600	50	-5	0.000006	81	0	0
	7-Dec-04	0.9583	305600	31	-16.4	0.000000	76	0	0
	7-Dec-05	0.9583	305600	37	-10.1	0.000000	70	0	0
	7-Dec-06	0.9583	305600	31	-3.5	0.000000	94	0	0
	7-Dec-07	0.9583	305600	31	-20.4	0.000074	89	0	0
	7-Dec-08	0.9583	305600	31	-7.2	0.000042	94	0	0
New Brunswick	23-Jul-94	0.7854	31550	41	30.3	0.000000	97	0	0
	23-Jul-95	0.7854	31550	37	25.5	0.000000	93	0	0
	23-Jul-97	0.7854	31550	31	22.4	0.000000	85	0	0
	23-Jul-98	0.7854	31550	31	27.3	0.000037	95	1	0
	23-Jul-99	0.7854	31550	46	25.7	0.000000	95	0	0
	23-Jul-00	0.7854	31550	37	22.8	0.000000	92	0	0
	23-Jul-01	0.7854	31550	44	31.6	0.000000	97	0	0
	23-Jul-02	0.7854	31550	54	31.7	0.000861	94	1	0
	23-Jul-03	0.7854	31550	31	24.4	0.000620	100	1	0
	23-Jul-04	0.7854	31550	50	28.4	0.000000	95	0	0

	23-Jul-05	0.7854	31550	56	22.2	0.001833	95	1	0
	23-Jul-06	0.7854	31550	33	21.2	0.000177	97	1	0
	23-Jul-07	0.7854	31550	31	26.3	0.000000	85	0	0
	23-Jul-08	0.7854	31550	31	23.4	0.000028	96	1	0
Quebec	2-Nov-92	0.8713	305600	31	-7.8	0.000000	85	0	0
	2-Nov-94	0.8713	305600	32	5.3	0.000386	100	0	0
	2-Nov-95	0.8713	305600	31	-7.9	0.000167	99	0	0
	2-Nov-96	0.8713	305600	31	-7.3	0.000000	74	0	0
	2-Nov-97	0.8713	305600	37	2.5	0.000496	100	0	0
	2-Nov-98	0.8713	305600	31	4.4	0.000194	100	0	0
	2-Nov-99	0.8713	305600	56	14.8	0.000000	90	0	0
	2-Nov-00	0.8713	305600	31	0.9	0.000000	89	0	0
	2-Nov-01	0.8713	305600	31	6.2	0.000000	91	0	0
	2-Nov-02	0.8713	305600	41	-4.6	0.000211	94	0	0
	2-Nov-03	0.8713	305600	37	-4	0.000000	82	0	0
	2-Nov-04	0.8713	305600	31	-0.6	0.000278	94	0	0
	2-Nov-05	0.8713	305600	50	11.3	0.000000	94	0	0
	2-Nov-06	0.8713	305600	31	-4	0.000000	96	0	0
	2-Nov-07	0.8713	305600	46	-6.1	0.000000	87	0	0
	2-Nov-08	0.8713	305600	41	-4.2	0.000019	86	0	0

DATASET I – Test Data

Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity (%)	Lightning	Actual Output	BPNN Model Predicted Outputs	GRNN Model Predicted Outputs	PNN Model Predicted Outputs
4-Nov-07	0.8712907	305600	61	-0.5	0.001366	97	0	1	0.992	0.929	0.964
4-Nov-94	0.8712907	305600	31	-2.2	0.000000	94	0	0	0.081	0	0.049
6-Jun-08	0.7362097	305600	32	20.5	0.000000	87	0	0	0.1	0.035	0.052
6-Jun-09	0.7362097	305600	35	23.9	0.000296	91	1	0	0.055	0.057	0.002
7-Jun-05	0.7362097	31550	50	24	0.000597	94	1	1	0.927	0.923	0.979
7-Jun-02	0.7362097	31550	31	13.5	0.000000	80	0	0	0.053	0.086	0.022
19-Jul-02	0.7853632	305600	31	19.8	0.000000	94	0	0	0.06	0.086	0.061
19-Jul-09	0.7853632	305600	31	24.1	0.000148	100	1	0	0.096	0.067	0.06
1-Aug-05	0.7760786	305600	31	19.6	0.000100	95	1	1	0.941	0.971	0.994
9-Aug-01	0.7760786	305600	31	29.9	0.000537	96	1	0	0.068	0.042	0.036
9-Aug-08	0.7760786	305600	31	20.1	0.000000	90	0	0	0.051	0.032	0.033
3-Feb-02	0.8975059	305600	31	-16.2	0.000000	82	0	0	0.075	0.083	0.038
10-Aug-03	0.7760786	305600	31	21.1	0.000151	97	1	1	0.935	0.961	0.987
26-Aug-01	0.7760786	305600	46	27.1	0.000122	99	1	0	0.067	0.08	0.007
28-Sep-03	0.7225560	31550	143	19.3	0.002639	96	1	1	0.941	0.951	0.997
28-Sep-92	0.7225560	31550	39	23.2	0.000194	97	1	0	0.005	0.027	0.022
26-Dec-01	0.9583106	305600	31	-5	0.000000	95	0	0	0.012	0	0.04
9-Mar-98	0.8860368	152000	48	-16.2	0.000833	98	0	0	0.035	0.003	0.073
9-Mar-04	0.8860368	152000	31	-10.3	0.000000	77	0	0	0.068	0.058	0.072
2-Aug-94	0.7760786	305600	31	20.9	0.000083	92	1	0	0.086	0.073	0.032
2-Aug-09	0.7760786	305600	31	26.8	0.000000	91	0	0	0.015	0.021	0.024
14-Aug-02	0.7760786	305600	31	28.5	0.000000	97	0	1	0.968	0.924	0.997
14-Aug-08	0.7760786	305600	31	19.6	0.000000	89	0	0	0.016	0.088	0.004
8-Sep-07	0.7225560	305600	33	30.4	0.000000	96	0	0	0.095	0.029	0.023
9-Sep-02	0.7225560	305600	31	30.3	0.000000	90	0	1	0.923	0.989	0.999
9-Sep-92	0.7225560	305600	31	16.3	0.000000	87	0	0	0.077	0.077	0.023
7-Nov-93	0.8712907	305600	32	-6.7	0.000000	90	0	0	0.075	0.078	0.018
7-Nov-94	0.8712907	305600	83	1.8	0.000107	100	0	0	0.04	0	0.039
7-Nov-09	0.8712907	305600	31	-5.8	0.000167	76	0	0	0.046	0.044	0.005
11-Jun-01	0.7362097	305600	31	23.2	0.000000	90	0	1	0.912	0.916	0.971
11-Jun-00	0.7362097	305600	31	15.1	0.000000	85	0	0	0.016	0.044	0.017
22-Jul-94	0.7853632	305600	31	28.1	0.000194	96	1	0	0.076	0.055	0.013
20-Dec-94	0.9583106	31550	37	-13.3	0.000000	88	0	0	0.032	0.051	0.054

20-Dec-95	0.9583106	31550	67	-12.6	0.000330	100	0	0	0.073	0.004	0.003
11-Jan-08	1.0000000	152000	61	-7.4	0.000075	95	0	0	0.079	0.085	0.006
11-Jan-09	1.0000000	152000	31	-19.7	0.000019	92	0	0	0.07	0.07	0.005
4-Mar-99	0.8860368	152000	67	-16	0.000000	80	0	1	0.97	0.974	0.997
4-Mar-08	0.8860368	152000	37	-13.1	0.000014	91	0	0	0.053	0.008	0.035
8-Jan-98	1.0000000	152000	65	-9.5	0.000048	87	0	1	0.91	0.923	0.962
25-Jun-00	0.7362097	152000	37	26.4	0.000889	97	1	0	0.096	0.085	0
25-Jun-01	0.7362097	152000	31	27.5	0.000000	93	0	0	0.061	0.062	0.044
4-Dec-94	0.9583106	305600	59	-6.3	0.000059	97	0	0	0.063	0.069	0.064
4-Dec-08	0.9583106	305600	48	-1.4	0.000000	91	0	0	0.104	0.039	0.056
4-Dec-09	0.9583106	305600	57	-7.3	0.000000	75	0	0	0.032	0.012	0.057
23-Jul-92	0.7853632	31550	31	22.5	0.000000	92	0	0	0.1	0.08	0.026
23-Jul-09	0.7853632	31550	31	21.3	0.000044	94	1	0	0.035	0.074	0.064
2-Nov-93	0.8712907	305600	46	-6.5	0.000239	98	0	1	0.939	0.965	0.98
2-Nov-09	0.8712907	305600	31	-4.3	0.000000	86	0	0	0.097	0.006	0.06
7-Dec-09	0.9583106	305600	33	-9.8	0.000000	80	0	0	0.097	0.017	0.034
2-Aug-96	0.7760786	305600	31	20.6	0.000000	82	0	0	0.018	0.023	0.049
9-Mar-05	0.8860368	152000	39	-19.9	0.000000	75	0	0	0.105	0.044	0.015
28-Sep-04	0.7225560	31550	33	10	0.000361	100	0	0	0.037	0.081	0.023
26-Aug-07	0.7760786	305600	31	21.9	0.000651	96	1	0	0.015	0.088	0.038
3-Feb-04	0.8975059	152000	15	-10.7	0.000000	96	0	0	0.023	0.06	0.073
3-Feb-03	0.8975059	152000	52	-14.4	0.000111	85	0	1	0.973	0.923	0.989
19-Jul-08	0.7853632	305600	31	25.1	0.000000	92	0	0	0.004	0.022	0.009
1-Aug-92	0.7760786	305600	48	12.8	0.000579	99	0	0	0.061	0.046	0.022
6-Jun-99	0.7362097	305600	48	24.1	0.000194	94	1	0	0.084	0.06	0.035
14-Nov-06	0.8712907	31800	46	8.7	0.000432	100	0	0	0.027	0.054	0.061
4-Nov-05	0.8712907	305600	41	-3.1	0.000000	79	0	0	0.104	0.089	0.037
6-Jun-00	0.7362097	305600	44	18.6	0.000000	96	0	0	0.044	0.061	0.004
19-Jul-95	0.7853632	305600	31	24.6	0.000144	100	1	0	0.064	0.014	0.072
1-Aug-02	0.7760786	305600	31	20.8	0.000000	95	0	0	0.07	0.005	0.02
3-Feb-07	0.8975059	152000	31	-20.1	0.000021	85	0	0	0.028	0.035	0.011
10-Aug-06	0.7760786	305600	31	21	0.000056	94	1	0	0.095	0.064	0.035
28-Sep-00	0.7225560	31550	32	5.1	0.000037	93	0	0	0.104	0.003	0.051
28-Sep-01	0.7225560	31550	31	6.5	0.000000	92	0	0	0.047	0.004	0.025
26-Dec-04	0.9583106	305600	31	-21.9	0.000111	71	0	0	0.052	0.075	0.039
26-Dec-09	0.9583106	305600	31	-12	0.000000	90	0	0	0.059	0	0.018
23-Jul-93	0.7853632	31550	31	19.2	0.000056	100	1	1	0.974	0.92	0.998

11-Jun-08	0.7362097	305600	31	23.5	0.000472	92	1	0	0.01	0.015	0.031
9-Mar-03	0.8860368	152000	41	-23.6	0.000024	81	0	0	0.078	0.055	0.04
2-Aug-97	0.7760786	305600	31	21.5	0.000398	100	1	0	0.017	0.017	0.072
14-Aug-98	0.7760786	305600	31	23.5	0.000000	100	0	0	0.099	0.037	0.025
8-Sep-04	0.7225560	305600	31	7.1	0.000167	90	0	0	0.095	0.058	0.063
9-Sep-96	0.7225560	152000	31	17.4	0.000071	100	1	0	0.052	0.017	0.014
7-Nov-01	0.8712907	305600	82	1.3	0.000068	93	0	0	0.097	0.014	0.066
11-Jun-09	0.7362097	305600	31	12	0.000025	95	0	0	0.043	0.049	0.07
21-Jul-95	0.7853632	305600	31	22.6	0.000083	100	1	0	0.025	0.007	0.008
10-Jul-04	0.7853632	305600	31	15.1	0.000014	91	0	0	0.023	0.015	0.073
22-Aug-96	0.7760786	152000	31	22.2	0.000576	100	1	0	0.071	0.034	0.062
17-Jul-08	0.7853632	305600	32	26.8	0.000133	91	1	0	0.084	0.061	0.002
22-Aug-01	0.7760786	152000	41	26.3	0.001167	98	1	0	0.032	0.085	0.022
24-Jul-03	0.7853632	305600	31	22.2	0.000175	97	1	0	0.041	0.047	0.038
10-Jul-97	0.7853632	305600	31	17.3	0.000000	100	0	0	0.087	0.084	0.022
13-Jul-06	0.7853632	152000	31	28.7	0.000000	97	0	0	0.082	0.023	0.038
20-Dec-99	0.9583106	31550	31	-11.5	0.000000	86	0	0	0.034	0.036	0.049
4-Mar-09	0.8860368	152000	31	-17.1	0.000000	80	0	0	0.013	0.021	0.041
11-Jan-04	1.0000000	152000	31	-16.2	0.000094	98	0	0	0.003	0.026	0.073
8-Jan-01	1.0000000	152000	31	-20.4	0.000011	74	0	0	0.04	0.044	0.028
2-Nov-91	0.8712907	305600	31	3.6	0.000293	100	0	0	0.038	0.066	0.072
17-Jul-99	0.7853632	305600	39	33.7	0.000000	85	0	0	0.021	0.089	0.029

DATASET II – Train Data

Provinces	Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity (%)	Lightning	Actual Output
Quebec	4-Nov-94	0.8712907	305600	17	-0.900000	0	86	0	0
	4-Nov-95	0.8712907	305600	19	-4.800000	4.861E-05	71	0	0
	4-Nov-96	0.8712907	305600	37	-6.600000	5.556E-05	57	0	0
	4-Nov-97	0.8712907	305600	28	3.700000	0.0002222	61	0	0
	4-Nov-99	0.8712907	305600	37	12.500000	0.0002037	92	0	0
	4-Nov-00	0.8712907	305600	7	3.800000	0.0001574	99	0	0
	4-Nov-01	0.8712907	305600	17	4.500000	0.0001429	81	0	0
	4-Nov-02	0.8712907	305600	17	-7.400000	0	83	0	0
	4-Nov-03	0.8712907	305600	35	-13.400000	0	41	0	0
	4-Nov-04	0.8712907	305600	28	-5.400000	0	61	0	0
	4-Nov-05	0.8712907	305600	28	-8.600000	0	56	0	0
	4-Nov-06	0.8712907	305600	19	-6.700000	0	42	0	0
	4-Nov-08	0.8712907	305600	15	-0.200000	0	64	0	0
Nova Scotia	4-Nov-09	0.8712907	31800	32	-6.100000	0	46	0	0
	14-Nov-04	0.8712907	31800	48	0.000000	0.0002614	100	0	1
	14-Nov-92	0.8712907	31800	22	-1.600000	9.375E-05	51	0	0
	14-Nov-94	0.8712907	31800	24	3.8	0	90	0	0
	14-Nov-96	0.8712907	31800	19	-5.800000	0	85	0	0
	14-Nov-97	0.8712907	31800	22	-8.400000	0.0002619	72	0	0
	14-Nov-98	0.8712907	31800	22	-8.600000	0	45	0	0
	14-Nov-99	0.8712907	31800	24	2.400000	0	87	0	0
	14-Nov-01	0.8712907	31800	20	-2.400000	4.444E-05	89	0	0
	14-Nov-02	0.8712907	31800	33	4.200000	0.0006185	99	0	0
	14-Nov-03	0.8712907	31800	39	1.900000	2.083E-05	86	0	0
	14-Nov-05	0.8712907	31800	30	1.900000	0	63	0	0
	14-Nov-06	0.8712907	31800	50	11.500000	0.0004316	99	0	0
	14-Nov-08	0.8712907	31800	39	9.700000	0.0003264	97	0	0
	14-Nov-09	0.8712907	31800	28	2.000000	0	63	0	0
	6-Jun-05	0.7362097	31800	22	-2.400000	0.0001204	28	0	1
Quebec	6-Jun-92	0.7362097	305600	24	10.700000	0.0001	90	0	0
	6-Jun-93	0.7362097	305600	19	8.300000	0	77	0	0
	6-Jun-94	0.7362097	305600	28	12.000000	0.0004074	47	0	0
	6-Jun-95	0.7362097	305600	28	2.100000	0.0003148	38	0	0
	6-Jun-96	0.7362097	305600	24	4.1	0	31	0	0
	6-Jun-97	0.7362097	305600	17	5.500000	0	63	0	0
	6-Jun-98	0.7362097	305600	22	5.100000	0	61	0	0
	6-Jun-00	0.7362097	305600	30	1.200000	0	36	0	0

	6-Jun-01	0.7362097	305600	20	8.800000	6.667E-05	81	0	0
	6-Jun-02	0.7362097	305600	22	7.300000	0	77	0	0
	6-Jun-03	0.7362097	305600	32	0.800000	0.0002302	34	0	0
	6-Jun-04	0.7362097	305600	28	6.700000	0	39	0	0
	6-Jun-06	0.7362097	305600	19	10.900000	0	69	0	0
	6-Jun-07	0.7362097	305600	30	14.600000	0	76	0	0
New Brunswick	6-Jun-08	0.7362097	31550	22	3.900000	0	42	0	0
	6-Jun-09	0.7362097	31550	26	6.200000	0.0002963	35	0	0
	7-Jun-05	0.7362097	31550	33	15.300000	0.0005972	61	0	1
	7-Jun-94	0.7362097	31550	28	13.200000	0.0003413	99	0	0
	7-Jun-95	0.7362097	31550	44	15.800000	0	67	0	0
	7-Jun-96	0.7362097	31550	30	11.400000	0.0002778	48	0	0
	7-Jun-97	0.7362097	31550	22	3.700000	0	46	0	0
	7-Jun-98	0.7362097	31550	28	4.2	0	50	0	0
	7-Jun-99	0.7362097	31550	32	12.100000	0	81	0	0
	7-Jun-00	0.7362097	31550	39	6.300000	0.0002917	99	0	0
	7-Jun-01	0.7362097	31550	15	10.500000	0.0008056	66	0	0
	7-Jun-02	0.7362097	31550	26	2.500000	0	50	0	0
	7-Jun-03	0.7362097	31550	26	9.600000	0	47	0	0
	7-Jun-04	0.7362097	31550	31	8.500000	0.000213	67	0	0
	7-Jun-06	0.7362097	31550	28	8.900000	2.381E-05	44	0	0
Quebec	7-Jun-07	0.7362097	305600	20	9.900000	8.333E-05	95	0	0
	7-Jun-09	0.7362097	305600	33	5.600000	0	39	0	0
	19-Jul-05	0.7853632	305600	22	18.900000	0	57	0	1
	19-Jul-92	0.7853632	305600	19	13.800000	0	59	0	0
	19-Jul-93	0.7853632	305600	19	10.200000	0	62	0	0
	19-Jul-94	0.7853632	305600	20	13.400000	0.0001111	68	0	0
	19-Jul-95	0.7853632	305600	22	15.800000	0.0001444	63	0	0
	19-Jul-96	0.7853632	305600	24	15.700000	0.0012361	92	0	0
	19-Jul-97	0.7853632	305600	20	13.300000	0	72	0	0
	19-Jul-98	0.7853632	305600	33	8.5	0	35	0	0
	19-Jul-00	0.7853632	305600	28	14.400000	0.0003796	59	0	0
	19-Jul-01	0.7853632	305600	17	12.600000	0	41	0	0
	19-Jul-02	0.7853632	305600	24	7.700000	0	47	0	0
	19-Jul-03	0.7853632	305600	19	16.600000	0.0005926	83	0	0
Quebec	19-Jul-04	0.7853632	305600	15	15.600000	7.778E-05	90	0	0
	19-Jul-08	0.7853632	305600	19	13.000000	0	49	0	0
	19-Jul-09	0.7853632	305600	24	16.500000	0.0001481	78	0	0
	1-Aug-05	0.7760786	305600	15	11.700000	0.0001	61	0	1
	1-Aug-92	0.7760786	305600	33	10.500000	0.0005789	94	0	0
	1-Aug-93	0.7760786	305600	22	17.700000	0	67	0	0

	1-Aug-94	0.7760786	305600	22	17.700000	0	83	0	0
	1-Aug-96	0.7760786	305600	19	12.400000	7.778E-05	57	0	0
	1-Aug-97	0.7760786	305600	28	17.200000	0.0001111	56	1	0
	1-Aug-98	0.7760786	305600	19	9.800000	0	53	0	0
	1-Aug-00	0.7760786	305600	17	16.300000	0	62	0	0
	1-Aug-01	0.7760786	305600	19	12.800000	0	39	0	0
	1-Aug-02	0.7760786	305600	17	11.1	0	56	0	0
	1-Aug-03	0.7760786	305600	15	17.000000	0	54	0	0
Quebec	1-Aug-04	0.7760786	305600	20	18.300000	0.0012037	54	1	0
	1-Aug-06	0.7760786	305600	30	13.000000	0	69	0	0
	1-Aug-07	0.7760786	305600	13	12.700000	0	56	0	0
	1-Aug-08	0.7760786	305600	30	14.500000	0.0003056	89	0	0
	1-Aug-09	0.7760786	305600	22	13.100000	0	44	0	0
	9-Aug-05	0.7760786	305600	37	9.300000	0	24	0	1
	9-Aug-92	0.7760786	305600	19	15.800000	0	47	0	0
	9-Aug-94	0.7760786	305600	22	13.900000	0	57	0	0
	9-Aug-95	0.7760786	305600	15	16.400000	0	41	0	0
	9-Aug-96	0.7760786	305600	19	17.700000	6.667E-05	64	1	0
	9-Aug-98	0.7760786	305600	28	19.800000	0	50	0	0
	9-Aug-99	0.7760786	305600	24	10.000000	0.0001548	67	0	0
	9-Aug-01	0.7760786	305600	20	15.800000	0.000537	44	0	0
	9-Aug-02	0.7760786	305600	22	11.400000	0	63	0	0
	9-Aug-03	0.7760786	305600	17	16.200000	0.0001111	85	0	0
Ontario	9-Aug-06	0.7760786	152000	20	9.9	0	44	0	0
	9-Aug-07	0.7760786	152000	28	12.100000	0.0003403	100	0	0
	9-Aug-08	0.7760786	152000	20	14.600000	0	78	0	0
	3-Feb-03	0.8975059	152000	35	-11.700000	0.0001111	76	0	1
	3-Feb-92	0.8975059	152000	13	-13.200000	0	87	0	0
	3-Feb-94	0.8975059	152000	28	-15.500000	6.197E-05	79	0	0
	3-Feb-95	0.8975059	152000	15	-14.800000	0	64	0	0
	3-Feb-96	0.8975059	152000	17	-28.900000	0	48	0	0
	3-Feb-97	0.8975059	152000	19	-8.600000	4.762E-05	93	0	0
	3-Feb-98	0.8975059	152000	26	-11.500000	1.389E-05	81	0	0
	3-Feb-01	0.8975059	152000	17	-22.000000	0.0001444	50	0	0
	3-Feb-02	0.8975059	152000	24	-5.200000	0	85	0	0
Quebec	3-Feb-04	0.8975059	305600	30	-7.100000	0	74	0	0
	3-Feb-06	0.8975059	305600	20	-1.300000	6.878E-05	94	0	0
	3-Feb-07	0.8975059	305600	20	-20.300000	2.083E-05	78	0	0
	3-Feb-08	0.8975059	305600	13	-5.200000	2.315E-05	93	0	0
	10-Aug-03	0.7760786	305600	19	16.500000	0.0001508	85	0	1
	10-Aug-92	0.7760786	305600	22	15.6	0	56	0	0

	10-Aug-93	0.7760786	305600	22	15.000000	0.0010185	79	0	0
	10-Aug-94	0.7760786	305600	17	15.800000	0	73	0	0
	10-Aug-95	0.7760786	305600	22	16.400000	0	55	0	0
	10-Aug-96	0.7760786	305600	19	13.200000	0	54	0	0
	10-Aug-97	0.7760786	305600	22	16.500000	0	77	0	0
	10-Aug-99	0.7760786	305600	32	8.500000	0	54	0	0
	10-Aug-00	0.7760786	305600	19	15.100000	0.0003963	97	0	0
	10-Aug-02	0.7760786	305600	28	15.000000	0	68	0	0
Quebec	10-Aug-05	0.7760786	305600	19	17.200000	0.0001296	72	1	0
	10-Aug-06	0.7760786	305600	26	12.700000	5.556E-05	66	0	0
	10-Aug-09	0.7760786	305600	9	16.100000	0.0001825	85	0	0
	26-Aug-03	0.7760786	305600	19	10.000000	0	60	0	1
	26-Aug-92	0.7760786	305600	11	12.600000	0.0005	91	0	0
	26-Aug-94	0.7760786	305600	19	14.700000	0	66	0	0
	26-Aug-96	0.7760786	305600	28	9.700000	0	61	0	0
	26-Aug-97	0.7760786	305600	24	15.400000	0.0003889	86	0	0
	26-Aug-98	0.7760786	305600	11	13.5	0.000142	97	0	0
	26-Aug-00	0.7760786	305600	22	15.700000		72	0	0
	26-Aug-01	0.7760786	305600	33	9.300000	0.0001222	34	0	0
	26-Aug-02	0.7760786	305600	22	10.500000	0.0001548	54	0	0
	26-Aug-04	0.7760786	305600	17	13.200000	0	49	0	0
	26-Aug-05	0.7760786	305600	22	5.600000	0	27	0	0
New Brunswick	26-Aug-06	0.7760786	31550	15	5.900000	0	50	0	0
	26-Aug-07	0.7760786	31550	17	13.100000	0.0006508	75	0	0
	28-Sep-92	0.7225560	31550	22	11.900000	0.0001944	51	0	0
	28-Sep-93	0.7225560	31550	48	18.700000	0.0005833	91	1	0
	28-Sep-94	0.7225560	31550	28	14.600000	0.0003636	86	0	0
	28-Sep-96	0.7225560	31550	26	10.600000	0	89	0	0
	28-Sep-97	0.7225560	31550	26	4.800000	0	57	0	0
	28-Sep-98	0.7225560	31550	32	15.700000	0.0009097	96	0	0
	28-Sep-99	0.7225560	31550	13	8.400000	0	69	0	0
	28-Sep-00	0.7225560	31550	24	6.900000	3.704E-05	80	0	0
Quebec	28-Sep-01	0.7225560	305600	19	5.600000	0	67	0	0
	28-Sep-04	0.7225560	305600	33	13	0.0003611	100	0	0
	28-Sep-05	0.7225560	305600	19	7.600000	0	93	0	0
	28-Sep-07	0.7225560	305600	44	18.100000	0	98	0	0
	28-Sep-08	0.7225560	305600	59	15.600000	0.001377	94	0	0
	26-Dec-03	0.9583106	305600	20	0.900000	0.0002556	95	0	1
	26-Dec-93	0.9583106	305600	22	-3.900000	0.0001715	93	0	0
	26-Dec-94	0.9583106	305600	30	-8.300000	1.389E-05	75	0	0
	26-Dec-95	0.9583106	305600	30	-8.300000	7.407E-05	75	0	0

	26-Dec-96	0.9583106	305600	22	-21.800000	0	54	0	0
	26-Dec-97	0.9583106	305600	6	-3.000000	6.481E-05	97	0	0
	26-Dec-98	0.9583106	305600	22	-5.600000	0	75	0	0
	26-Dec-99	0.9583106	305600	26	-1.900000	0	88	0	0
	26-Dec-00	0.9583106	305600	24	-17.600000	3.801E-05	71	0	0
Ontario	26-Dec-01	0.9583106	152000	11	-4.100000	0	84	0	0
	26-Dec-02	0.9583106	152000	26	-9.700000	1.691E-05	78	0	0
	26-Dec-04	0.9583106	152000	17	-21.900000	0.0001111	45	0	0
	26-Dec-08	0.9583106	152000	26	-22.900000	0	46	0	0
	26-Dec-09	0.9583106	152000	11	-7.2	0	76	0	0
	9-Mar-92	0.8860368	152000	30	5.300000	7.407E-05	100	0	0
	9-Mar-94	0.8860368	152000	9	-15.700000	0	72	0	0
	9-Mar-95	0.8860368	152000	24	-22.200000	0	43	0	0
	9-Mar-96	0.8860368	152000	26	-18.800000	0	49	0	0
	9-Mar-99	0.8860368	152000	20	-17.600000	0	41	0	0
	9-Mar-03	0.8860368	152000	30	-21.400000	2.381E-05	58	0	0
	9-Mar-04	0.8860368	152000	15	-11.600000	0	72	0	0
Quebec	9-Mar-05	0.8860368	305600	28	-19.800000	0	57	0	0
	9-Mar-06	0.8860368	305600	32	-2.900000	9.804E-05	89	0	0
	9-Mar-07	0.8860368	305600	26	-14.000000	0	51	0	0
	9-Mar-08	0.8860368	305600	41	-17.600000	5.556E-05	73	0	0
	9-Mar-09	0.8860368	305600	24	-12.600000	0.0002037	60	0	0
	2-Aug-92	0.7760786	305600	30	8.900000	7.407E-05	56	0	0
	2-Aug-94	0.7760786	305600	26	7.700000	8.333E-05	44	0	0
	2-Aug-96	0.7760786	305600	17	13.100000	0	74	0	0
	2-Aug-97	0.7760786	305600	24	16.100000	0.0003981	80	0	0
	2-Aug-98	0.7760786	305600	28	11.1	0.0001019	37	0	0
	2-Aug-99	0.7760786	305600	19	12.800000	0	62	0	0
	2-Aug-00	0.7760786	305600	19	14.000000	0.0001778	68	0	0
	2-Aug-01	0.7760786	305600	20	18.900000	0	52	0	0
	2-Aug-03	0.7760786	305600	30	15.400000	0	67	0	0
Quebec	2-Aug-04	0.7760786	305600	19	13.400000	0	60	0	0
	2-Aug-06	0.7760786	305600	26	11.700000	0	39	0	0
	2-Aug-08	0.7760786	305600	26	13.400000	8.333E-05	89	0	0
	2-Aug-09	0.7760786	305600	17	15.400000	0	51	0	0
	14-Aug-02	0.7760786	305600	17	20.100000	0	63	0	1
	14-Aug-92	0.7760786	305600	22	7.200000	0	50	0	0
	14-Aug-93	0.7760786	305600	19	16.100000	1.389E-05	78	0	0
	14-Aug-94	0.7760786	305600	15	17.300000	0.0001111	80	1	0
	14-Aug-96	0.7760786	305600	22	5.300000	0	56	0	0
	14-Aug-97	0.7760786	305600	19	14.600000	4.861E-05	100	0	0

	14-Aug-98	0.7760786	305600	22	12.400000	0	54	0	0
	14-Aug-99	0.7760786	305600	24	14.800000	0.0003819	96	0	0
	14-Aug-00	0.7760786	305600	11	16.2	0	72	0	0
	14-Aug-01	0.7760786	305600	20	8.000000	0	37	0	0
	14-Aug-03	0.7760786	305600	26	12.200000	0	57	0	0
Quebec	14-Aug-04	0.7760786	305600	31	18.700000	0.0001667	82	1	0
	14-Aug-05	0.7760786	305600	22	9.800000	0	55	0	0
	14-Aug-06	0.7760786	305600	32	6.900000	5.556E-05	43	0	0
	14-Aug-07	0.7760786	305600	24	10.200000	0	60	0	0
	14-Aug-08	0.7760786	305600	22	14.000000	0	71	0	0
	8-Sep-02	0.7225560	305600	20	11.100000	0.0004192	85	0	1
	8-Sep-92	0.7225560	305600	22	15.600000	0.0001111	81	0	0
	8-Sep-93	0.7225560	305600	19	11.100000	0	72	0	0
	8-Sep-94	0.7225560	305600	22	11.200000	2.778E-05	83	0	0
	8-Sep-96	0.7225560	305600	20	5.700000	0	50	0	0
	8-Sep-97	0.7225560	305600	15	14.300000	0	70	0	0
	8-Sep-98	0.7225560	305600	19	13.100000	6.349E-05	85	0	0
	8-Sep-00	0.7225560	305600	22	12.300000	0	47	0	0
	8-Sep-03	0.7225560	305600	24	5.300000	0	53	0	0
	8-Sep-04	0.7225560	305600	22	9.3	0.0001667	60	0	0
Ontario	8-Sep-05	0.7225560	152000	13	14.700000	0	60	0	0
	8-Sep-06	0.7225560	152000	20	11.800000	0	44	0	0
	8-Sep-07	0.7225560	152000	26	19.100000	0	61	0	0
	8-Sep-08	0.7225560	152000	15	14.200000	0.0002014	86	0	0
	8-Sep-09	0.7225560	152000	22	4.400000	0	38	0	0
	9-Sep-92	0.7225560	152000	19	9.900000	0	81	0	0
	9-Sep-95	0.7225560	152000	22	2.000000	0.0002778	81	0	0
	9-Sep-96	0.7225560	152000	13	14.400000	7.143E-05	97	0	0
	9-Sep-97	0.7225560	152000	15	13.000000	0	86	0	0
	9-Sep-08	0.7225560	152000	24	8.100000	0	93	0	0
	9-Sep-99	0.7225560	152000	20	10.900000	0	53	0	0
	9-Sep-00	0.7225560	152000	13	10.700000	0	44	0	0
	9-Sep-01	0.7225560	152000	20	20.300000	0.0002222	83	1	0
	9-Sep-03	0.7225560	152000	17	6.800000	0	83	0	0
	9-Sep-04	0.7225560	152000	19	7.400000	2.778E-05	73	0	0
Quebec	9-Sep-06	0.7225560	305600	22	2.200000	0	58	0	0
	9-Sep-07	0.7225560	305600	26	7.4	1.852E-05	86	0	0
	9-Sep-08	0.7225560	305600	22	6.700000	0.000381	64	0	0
	9-Sep-09	0.7225560	305600	17	9.200000	0	63	0	0
	7-Nov-92	0.8712907	305600	24	-5.500000	5.556E-06	73	0	0
	7-Nov-93	0.8712907	305600	22	-4.900000	0	70	0	0

	7-Nov-95	0.8712907	305600	22	-0.900000	0.0006111	62	0	0
	7-Nov-96	0.8712907	305600	19	0.700000	0.0001444	64	0	0
	7-Nov-97	0.8712907	305600	11	-3.400000	0	67	0	0
	7-Nov-98	0.8712907	305600	22	-3.600000	0	63	0	0
	7-Nov-99	0.8712907	305600	19	-4.700000	0	60	0	0
	7-Nov-00	0.8712907	305600	15	4.900000	1.736E-05	93	0	0
	7-Nov-01	0.8712907	305600	52	-4.600000	6.79E-05	53	0	0
	7-Nov-03	0.8712907	305600	17	-5.000000	0	55	0	0
Quebec	7-Nov-04	0.8712907	305600	24	-5.300000	4.762E-05	61	0	0
	7-Nov-05	0.8712907	305600	33	-1.400000	0.0002963	56	0	0
	7-Nov-06	0.8712907	305600	20	-3.000000	0	66	0	0
	7-Nov-07	0.8712907	305600	35	6.200000	0.0005754	97	0	0
	7-Nov-08	0.8712907	305600	17	2.9	0.0001296	97	0	0
	11-Jun-01	0.7362097	305600	20	9.600000	0	52	0	1
	11-Jun-92	0.7362097	305600	19	6.100000	0	48	0	0
	11-Jun-94	0.7362097	305600	41	3.900000	0	22	0	0
	11-Jun-95	0.7362097	305600	15	10.700000	0.0002222	92	0	0
	11-Jun-96	0.7362097	305600	26	11.200000	0	41	0	0
	11-Jun-98	0.7362097	305600	19	7.900000	0	30	0	0
	11-Jun-99	0.7362097	305600	19	14.600000	0	51	0	0
	11-Jun-00	0.7362097	305600	17	0.300000	0	48	0	0
	11-Jun-02	0.7362097	305600	22	8.000000	0.0011667	68	0	0
	11-Jun-03	0.7362097	305600	22	3.900000	0.0002917	37	0	0
	11-Jun-04	0.7362097	305600	35	0.300000	0	52	0	0
Quebec	11-Jun-05	0.7362097	305600	26	10.100000	0	60	0	0
	11-Jun-06	0.7362097	305600	19	12.500000	0.0003951	97	0	0
	11-Jun-08	0.7362097	305600	26	15.900000	0.0004722	65	0	0
	21-Jul-01	0.7853632	305600	17	17.800000	2.222E-05	54	1	1
	21-Jul-92	0.7853632	305600	22	15.100000	0.00025	62	0	0
	21-Jul-94	0.7853632	305600	20	17.1	0.0006296	52	1	0
	21-Jul-95	0.7853632	305600	19	14.000000	8.333E-05	63	0	0
	21-Jul-96	0.7853632	305600	19	8.700000	0.0004231	73	0	0
	21-Jul-97	0.7853632	305600	19	9.200000	2.778E-05	59	0	0
	21-Jul-98	0.7853632	305600	22	15.800000	0	63	0	0
	21-Jul-99	0.7853632	305600	24	10.000000	0	46	0	0
	21-Jul-00	0.7853632	305600	15	11.400000	0.0001667	67	0	0
	21-Jul-02	0.7853632	305600	30	10.600000	0	35	0	0
Quebec	21-Jul-03	0.7853632	305600	9	16.700000	7.143E-05	92	0	0
	21-Jul-05	0.7853632	305600	20	13.900000	0	51	0	0
	21-Jul-07	0.7853632	305600	19	13.700000	7.407E-05	68	0	0
	21-Jul-08	0.7853632	305600	19	16.300000	0.0003056	83	0	0

	22-Jul-01	0.7853632	305600	19	17.300000	2.778E-05	76	1	1
	22-Jul-92	0.7853632	305600	22	6.500000	0	50	0	0
	22-Jul-94	0.7853632	305600	20	18.600000	0.0001944	77	1	0
	22-Jul-95	0.7853632	305600	35	13.700000	0	87	0	0
	22-Jul-96	0.7853632	305600	33	8.100000	0	60	0	0
	22-Jul-97	0.7853632	305600	19	9.6	0	63	0	0
	22-Jul-98	0.7853632	305600	28	13.100000	0.0006889	57	0	0
	22-Jul-99	0.7853632	305600	20	16.100000	0.0001667	66	0	0
	22-Jul-00	0.7853632	305600	15	15.200000	0.0002963	71	0	0
	22-Jul-02	0.7853632	305600	28	17.800000	5.556E-05	53	1	0
	22-Jul-03	0.7853632	305600	15	14.900000	0.0001944	88	0	0
	22-Jul-04	0.7853632	305600	26	16.800000	0	57	0	0
	22-Jul-05	0.7853632	305600	17	13.700000	0.0002778	70	0	0
Quebec	22-Jul-06	0.7853632	305600	26	15.500000	0	70	0	0
	22-Jul-07	0.7853632	305600	20	8.700000	0	39	0	0
	22-Jul-08	0.7853632	305600	17	11.900000	0.0001	52	0	0
	22-Jul-09	0.7853632	305600	6	15.700000	0.0001543	91	0	0
	24-Jul-92	0.7853632	305600	17	14.800000	0	66	0	0
	24-Jul-93	0.7853632	305600	19	9.400000	0.0000625	77	0	0
	24-Jul-95	0.7853632	305600	20	15.900000	0.0011167	58	0	0
	24-Jul-96	0.7853632	305600	19	13.900000	0	56	0	0
	24-Jul-97	0.7853632	305600	20	10.200000	0	41	0	0
	24-Jul-98	0.7853632	305600	26	15.3	4.63E-05	83	0	0
	24-Jul-99	0.7853632	305600	28	10.300000	0	49	0	0
	24-Jul-00	0.7853632	305600	24	14.400000	0	79	0	0
	24-Jul-02	0.7853632	305600	22	5.700000	0	56	0	0
	24-Jul-04	0.7853632	305600	44	17.000000	0.0005873	93	0	0
	24-Jul-05	0.7853632	305600	24	8.700000	0	43	0	0
	24-Jul-06	0.7853632	305600	9	12.200000	0	54	0	0
	24-Jul-07	0.7853632	305600	22	14.900000	0	54	0	0
Quebec	24-Jul-08	0.7853632	305600	20	17.200000	0	77	0	0
	24-Jul-09	0.7853632	305600	19	12.000000	0	45	0	0
	10-Jul-00	0.7853632	305600	24	13.800000	0.0003542	98	0	1
	10-Jul-92	0.7853632	305600	22	12.300000	0.0001869	99	0	0
	10-Jul-93	0.7853632	305600	19	9.100000	0.0002037	52	0	0
	10-Jul-94	0.7853632	305600	20	17.200000	0.0006944	60	1	0
	10-Jul-96	0.7853632	305600	22	12.900000	0.0005741	74	0	0
	10-Jul-97	0.7853632	305600	26	13.200000	0	82	0	0
	10-Jul-98	0.7853632	305600	20	11.900000	0.0003194	90	0	0
	10-Jul-01	0.7853632	305600	19	15.5	2.381E-05	92	0	0
	10-Jul-02	0.7853632	305600	22	9.100000	0	57	0	0

	10-Jul-03	0.7853632	305600	30	5.600000	0	35	0	0
	10-Jul-04	0.7853632	305600	15	11.400000	1.389E-05	87	0	0
	10-Jul-05	0.7853632	305600	15	15.600000	0	83	0	0
	10-Jul-07	0.7853632	305600	7	14.600000	0.0001278	92	0	0
	10-Jul-08	0.7853632	305600	28	17.700000	0.0006852	80	1	0
Ontario	10-Jul-09	0.7853632	152000	19	13.400000	0	47	0	0
	13-Jul-00	0.7853632	152000	17	12.600000	0.0004722	58	0	1
	13-Jul-92	0.7853632	152000	13	12.600000	0	80	0	0
	13-Jul-95	0.7853632	152000	22	20.500000	2.778E-05	60	1	0
	13-Jul-96	0.7853632	152000	19	15.800000	8.333E-05	80	0	0
	13-Jul-97	0.7853632	152000	30	19.500000	0	63	0	0
	13-Jul-98	0.7853632	152000	30	13.200000	2.778E-05	42	0	0
	13-Jul-99	0.7853632	152000	22	12.900000	0	47	0	0
	13-Jul-02	0.7853632	152000	17	13.900000	0	47	0	0
	13-Jul-03	0.7853632	152000	19	9.000000	0	38	0	0
	13-Jul-05	0.7853632	152000	24	17.4	0	61	0	0
	13-Jul-06	0.7853632	152000	19	17.100000	0	53	0	0
	13-Jul-07	0.7853632	152000	22	9.300000	0.0004444	58	0	0
	13-Jul-08	0.7853632	152000	41	13.400000	0	57	0	0
	13-Jul-09	0.7853632	152000	20	6.700000	4.167E-05	82	0	0
	17-Jul-00	0.7853632	152000	22	13.900000	0.0004444	94	0	1
Quebec	17-Jul-92	0.7853632	305600	26	7.600000	0	60	0	0
	17-Jul-93	0.7853632	305600	24	8.900000	0.0001159	85	0	0
	17-Jul-95	0.7853632	305600	19	7.600000	0	54	0	0
	17-Jul-97	0.7853632	305600	28	18.000000	0.0005278	95	1	0
	17-Jul-98	0.7853632	305600	32	18.000000	0.0006296	71	1	0
	17-Jul-99	0.7853632	305600	28	14.300000	0	32	0	0
	17-Jul-02	0.7853632	305600	22	13.000000	0	47	0	0
	17-Jul-03	0.7853632	305600	17	17.100000	0	64	0	0
	17-Jul-04	0.7853632	305600	30	16.000000	0	79	0	0
	17-Jul-05	0.7853632	305600	20	17.200000	0	58	0	0
	17-Jul-06	0.7853632	305600	26	18.200000	0.0003056	78	1	0
	17-Jul-08	0.7853632	305600	19	17.6	0.0001333	68	1	0
	17-Jul-09	0.7853632	305600	17	14.600000	0.0001667	82	0	0
	22-Aug-92	0.7760786	305600	9	16.200000	0	64	0	0
Ontario	22-Aug-93	0.7760786	152000	19	10.200000	0	45	0	0
	22-Aug-94	0.7760786	152000	20	7.000000	0	79	0	0
	22-Aug-95	0.7760786	152000	20	8.100000	0	67	0	0
	22-Aug-96	0.7760786	152000	20	11.800000	0.0005764	97	0	0
	22-Aug-97	0.7760786	152000	19	11.600000	0.0001361	97	0	0
	22-Aug-98	0.7760786	152000	13	10.700000	0	59	0	0

	22-Aug-99	0.7760786	152000	17	12.000000	0	49	0	0
	22-Aug-01	0.7760786	152000	30	14.400000	0.0011667	50	0	0
	22-Aug-02	0.7760786	152000	19	14.600000	0.0004444	74	0	0
	22-Aug-05	0.7760786	152000	20	14.400000	0.0004444	93	0	0
	22-Aug-07	0.7760786	152000	17	8.600000	0	60	0	0
	22-Aug-09	0.7760786	152000	24	13.600000	0	97	0	0
	20-Dec-00	0.9583106	152000	78	-7.400000	0.0003351	79	0	1
	20-Dec-94	0.9583106	152000	28	-13.700000	0	75	0	0
	20-Dec-95	0.9583106	152000	44	0	0.0003299	99	0	0
	20-Dec-97	0.9583106	152000	26	-10.500000	0	68	0	0
New Brunswick	20-Dec-98	0.9583106	31550	35	-5.500000	1.111E-05	76	0	0
	20-Dec-99	0.9583106	31550	19	-13.600000	0	74	0	0
	20-Dec-01	0.9583106	31550	26	-9.300000	0	84	0	0
	20-Dec-03	0.9583106	31550	20	-12.200000	0	83	0	0
	20-Dec-04	0.9583106	31550	22	-0.600000	4.861E-05	99	0	0
	20-Dec-05	0.9583106	31550	33	-8.000000	2.778E-05	64	0	0
	20-Dec-06	0.9583106	31550	22	-14.100000	0	65	0	0
	20-Dec-07	0.9583106	31550	32	-9.600000	0	76	0	0
	20-Dec-08	0.9583106	31550	24	-15.400000	1.17E-05	75	0	0
	11-Jan-92	1.0000000	31550	20	-19.700000	0	89	0	0
	11-Jan-93	1.0000000	31550	15	-25.700000	0	47	0	0
	11-Jan-94	1.0000000	31550	26	-9.300000	3.704E-05	65	0	0
Ontario	11-Jan-95	1.0000000	152000	26	-20.000000	7.937E-05	74	0	0
	11-Jan-96	1.0000000	152000	11	-14.600000	0	75	0	0
	11-Jan-97	1.0000000	152000	19	-20.000000	1.634E-05	82	0	0
	11-Jan-98	1.0000000	152000	19	-15.6	5.556E-05	86	0	0
	11-Jan-02	1.0000000	152000	20	-6.300000	3.704E-05	80	0	0
	11-Jan-03	1.0000000	152000	22	-17.400000	1.208E-05	72	0	0
	11-Jan-04	1.0000000	152000	13	-19.200000	9.375E-05	81	0	0
	11-Jan-06	1.0000000	152000	20	1.800000	0.0002222	100	0	0
	11-Jan-07	1.0000000	152000	28	-6.600000	3.472E-05	60	0	0
	11-Jan-08	1.0000000	152000	41	-6.800000	7.488E-05	87	0	0
	4-Mar-99	0.8860368	152000	43	-14.300000	0	60	0	1
	4-Mar-92	0.8860368	152000	19	-9.000000	0	43	0	0
	4-Mar-93	0.8860368	152000	31	-11.700000	0	47	0	0
	4-Mar-94	0.8860368	152000	24	-5.600000	0	80	0	0
Ontario	4-Mar-95	0.8860368	152000	20	-12.200000	6.173E-06	79	0	0
	4-Mar-96	0.8860368	152000	28	-18.800000	0.0001667	48	0	0
	4-Mar-97	0.8860368	152000	22	-16.100000	5.556E-06	56	0	0
	4-Mar-98	0.8860368	152000	20	-2.200000	0	84	0	0
	4-Mar-02	0.8860368	152000	32	-20.300000	0	53	0	0

	4-Mar-03	0.8860368	152000	28	-8.500000	9.357E-05	86	0	0
	4-Mar-04	0.8860368	152000	15	-0.1	4.701E-05	100	0	0
	4-Mar-05	0.8860368	152000	28	-13.400000	0	47	0	0
	4-Mar-06	0.8860368	152000	37	-12.000000	0	43	0	0
	4-Mar-09	0.8860368	152000	17	-17.400000	0	34	0	0
	6-Jan-92	1.0000000	152000	19	0.500000	0.0003947	99	0	0
	6-Jan-93	1.0000000	152000	19	-13.500000	0	72	0	0
	6-Jan-94	1.0000000	152000	37	-25.300000	0	46	0	0
	6-Jan-96	1.0000000	152000	37	-14.900000	0	68	0	0
Quebec	6-Jan-97	1.0000000	305600	19	-10.700000	1.389E-05	83	0	0
	6-Jan-99	1.0000000	305600	22	-8.900000	0.0001181	86	0	0
	6-Jan-00	1.0000000	305600	22	-21.800000	0	45	0	0
	6-Jan-01	1.0000000	305600	7	-12.100000	0.000169	90	0	0
	6-Jan-02	1.0000000	305600	15	-4.900000	2.778E-05	76	0	0
	6-Jan-03	1.0000000	305600	7	-18.800000	0	86	0	0
	6-Jan-05	1.0000000	305600	20	-26.400000	0	54	0	0
	6-Jan-06	1.0000000	305600	11	-3.500000	3.509E-05	97	0	0
	6-Jan-07	1.0000000	305600	7	0.100000	0.0001343	92	0	0
	6-Jan-08	1.0000000	305600	11	-6.8	8.333E-05	92	0	0
	6-Jan-09	1.0000000	305600	43	-18.900000	0	46	0	0
	8-Jan-98	1.0000000	305600	33	-9.600000	4.798E-05	84	0	1
	8-Jan-92	1.0000000	305600	19	-16.200000	0	61	0	0
	8-Jan-93	1.0000000	305600	19	-24.400000	0	59	0	0
	8-Jan-94	1.0000000	305600	22	-27.100000	0	59	0	0
	8-Jan-95	1.0000000	305600	35	-9.500000	5.983E-05	86	0	0
	8-Jan-96	1.0000000	305600	15	-17.000000	5.556E-05	57	0	0
	8-Jan-97	1.0000000	305600	19	-18.000000	0	74	0	0
Ontario	8-Jan-99	1.0000000	152000	15	-12.500000	2.778E-05	89	0	0
	8-Jan-01	1.0000000	152000	20	-23.000000	1.111E-05	69	0	0
	8-Jan-02	1.0000000	152000	26	-3.000000	5.556E-05	93	0	0
	8-Jan-04	1.0000000	152000	19	-26.600000	2.222E-05	53	0	0
	8-Jan-05	1.0000000	152000	19	-5.800000	2.646E-06	87	0	0
	8-Jan-06	1.0000000	152000	15	-7.900000	1.852E-05	91	0	0
	8-Jan-07	1.0000000	152000	32	-5.900000	0.0001561	83	0	0
	8-Jan-08	1.0000000	152000	22	7.600000	0.0003675	100	0	0
	8-Jan-09	1.0000000	152000	28	-16.6	5.556E-06	76	0	0
	25-Jun-98	0.7362097	152000	20	20.200000	0.0009028	77	1	1
	25-Jun-92	0.7362097	152000	15	3.100000	0	30	0	0
	25-Jun-94	0.7362097	152000	37	12.100000	0.0004327	93	0	0
	25-Jun-95	0.7362097	152000	19	13.900000	3.333E-05	61	0	0
	25-Jun-96	0.7362097	152000	24	8.100000	0.0002778	47	0	0

	25-Jun-97	0.7362097	152000	32	16.700000	0.0006667	65	0	0
Ontario	25-Jun-00	0.7362097	152000	28	14.000000	0.0008889	47	0	0
	25-Jun-01	0.7362097	152000	31	13.300000	0	50	0	0
	25-Jun-02	0.7362097	152000	22	16.800000	0.0005	66	0	0
	25-Jun-03	0.7362097	152000	19	18.000000	0	45	0	0
	25-Jun-04	0.7362097	152000	30	1.800000	0	39	0	0
	25-Jun-05	0.7362097	152000	19	12.200000	0	40	0	0
	25-Jun-06	0.7362097	152000	13	12.400000	0	51	0	0
	25-Jun-08	0.7362097	152000	32	14.800000	0	55	0	0
	4-Dec-97	0.9583106	152000	22	-2.900000	0.0001667	65	0	1
	4-Dec-92	0.9583106	152000	28	-5.200000	3.758E-05	69	0	0
	4-Dec-93	0.9583106	152000	9	-0.3	0	97	0	0
	4-Dec-94	0.9583106	152000	28	-3.800000	5.926E-05	75	0	0
	4-Dec-95	0.9583106	152000	17	-6.600000	4.798E-05	89	0	0
	4-Dec-96	0.9583106	152000	15	-5.300000	0	73	0	0
Quebec	4-Dec-98	0.9583106	305600	28	-8.800000	0.000125	74	0	0
	4-Dec-99	0.9583106	305600	13	-4.600000	0	67	0	0
	4-Dec-00	0.9583106	305600	11	-6.800000	0	93	0	0
	4-Dec-01	0.9583106	305600	20	-6.500000	0	71	0	0
	4-Dec-02	0.9583106	305600	26	-12.400000	0	67	0	0
	4-Dec-03	0.9583106	305600	22	-10.800000	5.926E-05	69	0	0
	4-Dec-04	0.9583106	305600	19	-14.900000	0.0004583	60	0	0
	4-Dec-05	0.9583106	305600	37	-13.000000	0.000538	47	0	0
	4-Dec-06	0.9583106	305600	15	-8.900000	0.0002245	79	0	0
	4-Dec-07	0.9583106	305600	39	-3.600000	0	83	0	0
	4-Dec-09	0.9583106	305600	7	-2.900000	0	91	0	0
	7-Dec-97	0.9583106	305600	19	0.100000	0.0001304	98	0	1
	7-Dec-93	0.9583106	305600	13	-10.800000	3.819E-05	89	0	0
	7-Dec-96	0.9583106	305600	19	-2.2	2.924E-06	90	0	0
	7-Dec-98	0.9583106	305600	46	-10.000000	0.0002346	55	0	0
Quebec	7-Dec-99	0.9583106	305600	15	-1.800000	0.0001405	94	0	0
	7-Dec-00	0.9583106	305600	24	-15.500000	0	67	0	0
	7-Dec-02	0.9583106	305600	20	-7.500000	0	66	0	0
	7-Dec-03	0.9583106	305600	33	-5.500000	5.556E-06	77	0	0
	7-Dec-04	0.9583106	305600	24	-18.200000	0	59	0	0
	7-Dec-05	0.9583106	305600	33	-14.500000	0	49	0	0
	7-Dec-06	0.9583106	305600	1	-4.200000	0	75	0	0
	7-Dec-07	0.9583106	305600	15	-20.900000	7.407E-05	78	0	0
	7-Dec-08	0.9583106	305600	19	-2.300000	4.248E-05	83	0	0
	7-Dec-09	0.9583106	305600	33	-9.600000	0	61	0	0
	23-Jul-93	0.7853632	305600	19	15.100000	5.556E-05	90	0	1

	23-Jul-92	0.7853632	305600	26	9.900000	0	47	0	0
	23-Jul-94	0.7853632	305600	30	18.700000	0	53	0	0
	23-Jul-95	0.7853632	305600	22	19.900000	0	81	0	0
New Brunswick	23-Jul-97	0.7853632	31550	19	8.500000	0	45	0	0
	23-Jul-98	0.7853632	31550	20	10.8	3.704E-05	38	0	0
	23-Jul-99	0.7853632	31550	37	17.800000	0	71	0	0
	23-Jul-00	0.7853632	31550	33	11.900000	0	58	0	0
	23-Jul-01	0.7853632	31550	30	19.100000	0	55	0	0
	23-Jul-03	0.7853632	31550	17	18.500000	0.0006204	100	1	0
	23-Jul-05	0.7853632	31550	20	14.300000	0.0018333	88	0	0
	23-Jul-06	0.7853632	31550	24	18.600000	0.0001771	95	1	0
	23-Jul-07	0.7853632	31550	22	12.400000	0	45	0	0
	23-Jul-08	0.7853632	31550	19	17.700000	2.778E-05	75	1	0
	23-Jul-09	0.7853632	31550	20	14.900000	4.444E-05	95	0	0
	2-Nov-93	0.8712907	31550	28	-1.400000	0.0002389	92	0	1
	2-Nov-91	0.8712907	31550	7	7.200000	0.0002929	100	0	0
	2-Nov-92	0.8712907	31550	22	-8.000000	0	57	0	0
Quebec	2-Nov-94	0.8712907	305600	22	5.300000	0.0003864	99	0	0
	2-Nov-95	0.8712907	305600	22	-6.600000	0.0001667	49	0	0
	2-Nov-97	0.8712907	305600	28	9.100000	0.0004963	100	0	0
	2-Nov-98	0.8712907	305600	28	4.900000	0.0001944	98	0	0
	2-Nov-99	0.8712907	305600	33	5.4	0	56	0	0
	2-Nov-00	0.8712907	305600	15	0.300000	0	78	0	0
	2-Nov-01	0.8712907	305600	15	5.100000	0	80	0	0
	2-Nov-02	0.8712907	305600	24	-1.500000	0.0002111	94	0	0
	2-Nov-03	0.8712907	305600	26	-6.000000	0	50	0	0
	2-Nov-05	0.8712907	305600	30	-6.300000	0	48	0	0
	2-Nov-06	0.8712907	305600	15	-0.200000	0	61	0	0
	2-Nov-07	0.8712907	305600	33	-3.200000	0	52	0	0
	2-Nov-08	0.8712907	305600	26	-9.200000	1.852E-05	44	0	0
	2-Nov-09	0.8712907	305600	20	-4.300000	0	53	0	0

DATASET II- Test Train

Provinces	Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity (%)	Lightning	BPNN Model Predicted Outputs	GRNN Model Predicted Outputs	PNN Model Predicted Outputs
Quebec	4-Nov-98	0.8712907	305600	9	3.6	0.000173	93	0	0.148	0.07	0.039
Quebec	14-Nov-93	0.8712907	305600	28	5.9	0.000356	97	0	0.035	0.032	0.084
Quebec	6-Jun-99	0.7362097	305600	37	11.7	0.000194	46	0	0.144	0.022	0.123
Quebec	7-Jun-92	0.7362097	305600	24	13.7	0.000346	91	0	0.015	0.085	0.041
New Brunswick	7-Jun-08	0.7362097	31550	32	4.9	0.000000	64	0	0.114	0.059	0.047
New Brunswick	19-Jul-07	0.7853632	31550	13	14.8	0.000157	60	0	0.136	0.11	0.061
Quebec	1-Aug-95	0.7760786	305600	28	17.7	0.001074	61	1	0.066	0.017	0.102
Quebec	9-Aug-97	0.7760786	305600	20	14.7	0.000000	51	0	0.109	0.068	0.026
Quebec	9-Aug-09	0.7760786	305600	22	11.9	0.000000	55	0	0.155	0.061	0.089
Quebec	3-Feb-99	0.8975059	305600	28	-0.6	0.000000	99	0	0.089	0.099	0.025
Quebec	10-Aug-07	0.7760786	305600	19	9.8	0.000000	35	0	0.1	0.126	0.103
Ontario	36398	0.77607865	305600	17	16.9	0	73	0	0.118	0.078	0.114
Quebec	28-Sep-03	0.7225560	305600	78	18.6	0.002639	92	1	0.998	0.89	0.927
Quebec	28-Sep-09	0.7225560	305600	37	14.8	0.000907	97	0	0.094	0.112	0.121
New Brunswick	9-Mar-02	0.8860368	31550	57	-3	0.000125	81	0	0.931	0.913	0.961
New Brunswick	9-Mar-98	0.8860368	31550	39	-16.6	0.000833	76	0	0.126	0.085	0.049
Quebec	2-Aug-95	0.7760786	305600	22	7	0.000130	44	0	0.067	0.007	0.125
Ontario	2-Aug-05	0.7760786	152000	17	14.3	0.000000	83	0	0.051	0.039	0.042
Ontario	8-Sep-95	0.7225560	152000	22	5.5	0.000101	66	0	0.145	0.096	0.045
Quebec	9-Sep-93	0.7225560	305600	35	12.7	0.000421	94	0	0.061	0.022	0.078
Quebec	7-Nov-02	0.8712907	305600	30	-8.8	0.000042	69	0	0.939	0.896	0.904
Quebec	11-Jun-97	0.7362097	305600	30	-1	0.000000	26	0	0.158	0.017	0.023
Quebec	21-Jul-06	0.7853632	305600	17	18.2	0.000056	86	1	0.015	0.059	0.014
Quebec	34172	0.78536319	305600	13	14.4	0.00033333	86	0	0.081	0.013	0.071
Quebec	24-Jul-01	0.7853632	305600	24	17.6	0.000375	75	1	0.856	0.971	1
Quebec	10-Jul-95	0.7853632	305600	19	16.8	0.000000	63	0	0.179	0.132	0.071
Quebec	13-Jul-94	0.7853632	305600	31	8.2	0.000000	82	0	0.146	0.089	0.047
Quebec	17-Jul-94	0.7853632	305600	22	11.7	0.000000	66	0	0.029	0.143	0.079
Quebec	22-Aug-00	0.7760786	305600	28	13.6	0.000167	75	0	0.981	0.889	0.982
Quebec	22-Aug-08	0.7760786	305600	20	19	0.000000	59	0	0.174	0.088	0.036

Quebec	20-Dec-02	0.9583106	305600	30	0.8	0.000093	96	0	0.164	0.129	0.014
Quebec	11-Jan-09	1.0000000	305600	11	-14.2	0.000019	74	0	0.1	0.121	0.049
New Brunswick	4-Mar-07	0.8860368	31550	26	-13.9	0.000040	65	0	0.161	0.141	0.123
New Brunswick	6-Jan-98	1.0000000	31550	15	-12.8	0.000028	76	0	0.942	0.899	0.999
Ontario	6-Jan-04	1.0000000	152000	11	-14.9	0.000056	73	0	0.176	0.137	0.075
Ontario	37629	1	152000	32	-9.7	9.1503E-05	72	0	0.033	0.102	0.118
Ontario	25-Jun-07	0.7362097	152000	28	15.7	0.001556	52	0	0.174	0.066	0.01
Ontario	4-Dec-08	0.9583106	152000	24	-0.7	0.000000	77	0	0.084	0.077	0.044
Ontario	23-Jul-02	0.7853632	152000	37	19.9	0.000861	52	1	0.032	0.089	0.043
Ontario	2-Nov-96	0.8712907	152000	19	-4.8	0.000000	53	0	0.036	0.016	0.021
Ontario	4-Mar-01	0.8860368	152000	33	-15.9	0.000028	38	0	0.109	0.088	0.043
Quebec	11-Jan-05	1.0000000	305600	20	-15.8	0.000000	66	0	0.171	0.109	0.068
Quebec	22-Aug-06	0.7760786	305600	15	13	0.000167	75	0	0.057	0.012	0.056
Quebec	13-Jul-04	0.7853632	305600	17	17.8	0.000000	62	0	0.126	0.062	0.055
New Brunswick	24-Jul-03	0.7853632	31550	19	14.4	0.000175	68	0	0.038	0.146	0.034
New Brunswick	11-Jun-09	0.7362097	31550	20	6.8	0.000025	74	0	0.149	0.08	0.024
Quebec	7-Nov-09	0.8712907	305600	19	-9.4	0.000167	54	0	0.053	0.099	0.033
Quebec	37508	0.72255598	305600	22	16.3	0	48	0	0.895	0.862	0.953
Quebec	9-Mar-01	0.8860368	305600	11	-6.3	0.000028	72	0	0.042	0.143	0.059
Quebec	2-Aug-02	0.7760786	305600	15	12.3	0.000250	56	0	0.951	0.922	0.879
Ontario	26-Aug-08	0.7760786	152000	20	10.7	0.000000	63	0	0.015	0.012	0.085
New Brunswick	3-Feb-05	0.8975059	31550	20	-5.7	0.000000	68	0	0.12	0.025	0.117
Quebec	9-Aug-00	0.7760786	305600	19	15.6	0.000290	86	0	0.119	0.072	0.031
Ontario	19-Jul-99	0.7853632	152000	24	11.1	0.001083	67	0	0.149	0.079	0.038
Ontario	14-Nov-07	0.8712907	152000	30	3.6	0.000000	95	0	0.051	0.042	0.122
Quebec	9-Aug-04	0.7760786	305600	15	13.7	0.001667	75	0	0.082	0.08	0.064
Quebec	3-Feb-09	0.8975059	305600	24	-23.5	0.000011	63	0	0	0.032	0.087
Quebec	26-Aug-95	0.7760786	305600	28	3.5	0.000000	46	0	0.159	0.095	0.053
Nova Scotia	26-Dec-06	0.9583106	31800	11	-9.4	0.000050	71	0	0.115	0.128	0.057
Quebec	35498	0.88603677	305600	30	-12.1	0	54	0	0.103	0.078	0.079
Quebec	2-Aug-93	0.7760786	305600	15	17.2	0.000000	70	0	0.105	0.125	0.117
Quebec	14-Aug-95	0.7760786	305600	15	2.5	0.000000	33	0	0.071	0.091	0.118
Quebec	8-Sep-01	0.7225560	305600	17	16.8	0.000000	64	0	0.053	0.071	0.094

Ontario	7-Nov-94	0.8712907	152000	46	-1.4	0.000107	78	0	0.068	0.145	0.039
Quebec	11-Jun-93	0.7362097	305600	24	7.7	0.000000	79	0	0.077	0.034	0.067
New Brunswick	11-Jun-07	0.7362097	31550	17	14.2	0.000000	63	0	0.052	0.014	0.028
New Brunswick	13-Jul-01	0.7853632	31550	24	12.6	0.000000	70	0	0.016	0.144	0.089
Quebec	11-Jan-99	1.0000000	305600	22	-25	0.000100	61	0	0.894	0.917	0.921
Quebec	11-Jan-01	1.0000000	305600	24	-11.2	0.000000	61	0	0.127	0.134	0.023
New Brunswick	6-Jan-95	1.0000000	31550	22	-11.5	0.000000	65	0	0.123	0.102	0.042
Quebec	25-Jun-99	0.7362097	305600	22	14.4	0.000000	47	0	0.088	0.005	0.029
Ontario	35040	0.95831058	152000	28	-8.5	0	76	0	0.156	0.122	0.053
Quebec	23-Jul-04	0.7853632	305600	41	18.6	0.000000	62	0	0.135	0.041	0.072
Quebec	2-Nov-04	0.8712907	305600	13	-3.7	0.000278	69	0	0.099	0.076	0.013
Quebec	4-Mar-08	0.8860368	305600	28	-17.4	0.000014	58	0	0.139	0.145	0.032
Ontario	20-Dec-09	0.9583106	152000	37	-5.5	0.000076	83	0	0.064	0.009	0.054
Quebec	22-Aug-04	0.7760786	305600	32	8.4	0.001417	53	0	0.065	0.056	0.028
Quebec	17-Jul-01	0.7853632	305600	24	9.5	0.000000	55	0	0.092	0.008	0.08
Quebec	10-Jul-06	0.7853632	305600	17	15.2	0.000032	69	0	0.11	0.023	0.076
Quebec	24-Jul-94	0.7853632	305600	17	16.9	0.000896	95	0	0.145	0.022	0.115
Ontario	21-Jul-09	0.785363	152000	22	13	0.000000	54	0	0.031	0.015	0.043
Quebec	9-Sep-05	0.7225560	305600	17	4.8	0.000000	45	0	0.129	0.082	0.087
Ontario	14-Aug-09	0.7760786	152000	24	16.8	0.000056	56	0	0.062	0.101	0.055
Quebec	39296	0.77607865	305600	13	17.6	0.00048611	91	1	0.052	0.136	0.066
Quebec	26-Dec-07	0.9583106	305600	20	-9.5	0.000000	63	0	0.162	0.036	0.038
Ontario	10-Aug-08	0.7760786	152000	19	14.3	0.000000	80	0	0.081	0	0.076
New Brunswick	26-Aug-09	0.7760786	31550	35	10.1	0.000000	42	0	0.021	0.076	0.033
Ontario	14-Nov-00	0.8712907	152000	17	6.6	0.000004	98	0	0.08	0.038	0.123
Ontario	4-Nov-07	0.8712907	152000	48	1.7	0.001366	92	0	0.908	0.878	0.888
Ontario	10-Aug-98	0.7760786	152000	20	20.9	0.000000	52	0	0.149	0.036	0.06
Quebec	26-Dec-05	0.9583106	305600	26	-9.1	0.000271	89	0	0.116	0.107	0.043
Quebec	9-Sep-94	0.7225560	305600	22	6	0.000333	68	0	0.16	0.132	0.076

Sensitivity Analysis Dataset

No.	Consumption Index	Network Size	Wind Speed	Temperature	Precipitation	Lightning	Humidity	Predicted Output	Normalized Inputs
	0.83	231307.99	36.48	10.22	0.00	0.23	91.64		
1	0.72	231307.99	36.48	10.22	0.00	0.23	91.64	0.24	0
2	0.75	231307.99	36.48	10.22	0.00	0.23	91.64	0.27	0.1
3	0.78	231307.99	36.48	10.22	0.00	0.23	91.64	0.324	0.2
4	0.81	231307.99	36.48	10.22	0.00	0.23	91.64	0.374	0.3
5	0.83	231307.99	36.48	10.22	0.00	0.23	91.64	0.421	0.4
6	0.86	231307.99	36.48	10.22	0.00	0.23	91.64	0.44	0.5
7	0.89	231307.99	36.48	10.22	0.00	0.23	91.64	0.485	0.6
8	0.92	231307.99	36.48	10.22	0.00	0.23	91.64	0.513	0.7
9	0.94	231307.99	36.48	10.22	0.00	0.23	91.64	0.543	0.8
10	0.97	231307.99	36.48	10.22	0.00	0.23	91.64	0.565	0.9
11	1.00	231307.99	36.48	10.22	0.00	0.23	91.64	0.58	1
1	0.83	31550.00	36.48	10.22	0.00	0.23	91.64	0.189	0
2	0.83	58955.00	36.48	10.22	0.00	0.23	91.64	0.21	0.1
3	0.83	86360.00	36.48	10.22	0.00	0.23	91.64	0.226	0.2
4	0.83	113765.00	36.48	10.22	0.00	0.23	91.64	0.252	0.3
5	0.83	141170.00	36.48	10.22	0.00	0.23	91.64	0.253	0.4
6	0.83	168575.00	36.48	10.22	0.00	0.23	91.64	0.267	0.5
7	0.83	195980.00	36.48	10.22	0.00	0.23	91.64	0.291	0.6
8	0.83	223385.00	36.48	10.22	0.00	0.23	91.64	0.294	0.7
9	0.83	250790.00	36.48	10.22	0.00	0.23	91.64	0.321	0.8
10	0.83	278195.00	36.48	10.22	0.00	0.23	91.64	0.376	0.9
11	0.83	305600.00	36.48	10.22	0.00	0.23	91.64	0.417	1
1	0.83	231307.99	15.00	10.22	0.00	0.23	91.64	0.321	0
2	0.83	231307.99	27.80	10.22	0.00	0.23	91.64	0.346	0.1
3	0.83	231307.99	40.60	10.22	0.00	0.23	91.64	0.367	0.2
4	0.83	231307.99	53.40	10.22	0.00	0.23	91.64	0.441	0.3
5	0.83	231307.99	66.20	10.22	0.00	0.23	91.64	0.51	0.4
6	0.83	231307.99	79.00	10.22	0.00	0.23	91.64	0.536	0.5
7	0.83	231307.99	91.80	10.22	0.00	0.23	91.64	0.63	0.6
8	0.83	231307.99	104.60	10.22	0.00	0.23	91.64	0.67	0.7
9	0.83	231307.99	117.40	10.22	0.00	0.23	91.64	0.74	0.8
10	0.83	231307.99	130.20	10.22	0.00	0.23	91.64	0.82	0.9
11	0.83	231307.99	143.00	10.22	0.00	0.23	91.64	0.894	1
1	0.83	231307.99	36.48	-29.50	0.00	0.23	91.64	0.62	0
2	0.83	231307.99	36.48	-23.14	0.00	0.23	91.64	0.61	0.1
3	0.83	231307.99	36.48	-16.78	0.00	0.23	91.64	0.58	0.2
4	0.83	231307.99	36.48	-10.42	0.00	0.23	91.64	0.54	0.3

5	0.83	231307.99	36.48	-4.06	0.00	0.23	91.64	0.36	0.4
6	0.83	231307.99	36.48	2.30	0.00	0.23	91.64	0.294	0.5
7	0.83	231307.99	36.48	8.66	0.00	0.23	91.64	0.253	0.6
8	0.83	231307.99	36.48	15.02	0.00	0.23	91.64	0.31	0.7
9	0.83	231307.99	36.48	21.38	0.00	0.23	91.64	0.36	0.8
10	0.83	231307.99	36.48	27.74	0.00	0.23	91.64	0.46	0.9
11	0.83	231307.99	36.48	34.10	0.00	0.23	91.64	0.66	1
1	0.83	231307.99	36.48	10.22	0.000000	0.23	91.64	0.289	0
2	0.83	231307.99	36.48	10.22	0.000264	0.23	91.64	0.3	0.1
3	0.83	231307.99	36.48	10.22	0.000528	0.23	91.64	0.341	0.2
4	0.83	231307.99	36.48	10.22	0.000792	0.23	91.64	0.392	0.3
5	0.83	231307.99	36.48	10.22	0.001056	0.23	91.64	0.462	0.4
6	0.83	231307.99	36.48	10.22	0.001319	0.23	91.64	0.486	0.5
7	0.83	231307.99	36.48	10.22	0.001583	0.23	91.64	0.536	0.6
8	0.83	231307.99	36.48	10.22	0.001847	0.23	91.64	0.563	0.7
9	0.83	231307.99	36.48	10.22	0.002111	0.23	91.64	0.632	0.8
10	0.83	231307.99	36.48	10.22	0.002375	0.23	91.64	0.675	0.9
11	0.83	231307.99	36.48	10.22	0.002639	0.23	91.64	0.701	1
1	0.83	231307.99	36.48	10.22	0.00	0.00	91.64	0.214	0
2	0.83	231307.99	36.48	10.22	0.00	1.00	91.64	0.446	1
1	0.83	231307.99	36.48	10.22	0.00	0.23	50.000	0.157	0
2	0.83	231307.99	36.48	10.22	0.00	0.23	55.000	0.164	0.1
3	0.83	231307.99	36.48	10.22	0.00	0.23	60.000	0.169	0.2
4	0.83	231307.99	36.48	10.22	0.00	0.23	65.000	0.173	0.3
5	0.83	231307.99	36.48	10.22	0.00	0.23	70.000	0.18	0.4
6	0.83	231307.99	36.48	10.22	0.00	0.23	75.000	0.192	0.5
7	0.83	231307.99	36.48	10.22	0.00	0.23	80.000	0.21	0.6
8	0.83	231307.99	36.48	10.22	0.00	0.23	85.000	0.24	0.7
9	0.83	231307.99	36.48	10.22	0.00	0.23	90.000	0.28	0.8
10	0.83	231307.99	36.48	10.22	0.00	0.23	95.000	0.3	0.9
11	0.83	231307.99	36.48	10.22	0.00	0.23	100.00	0.32	1

Quebec Dataset I – Train

Province	Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity (%)	Lightning	Actual Output
Quebec	4-Nov-95	0.8712907	305600	31	-1.7	0.000049	100	0	0
	4-Nov-96	0.8712907	305600	56	-3.4	0.000056	72	0	0
	4-Nov-97	0.8712907	305600	31	4.6	0.000222	100	0	0
	4-Nov-98	0.8712907	305600	31	1.8	0.000173	99	0	0
	4-Nov-99	0.8712907	305600	54	2.1	0.000204	97	0	0
	4-Nov-00	0.8712907	305600	31	1.4	0.000157	100	0	0
	4-Nov-01	0.8712907	305600	31	3.6	0.000143	97	0	0
	4-Nov-02	0.8712907	305600	31	-8.3	0.000000	92	0	0
	4-Nov-03	0.8712907	305600	57	-3.8	0.000000	67	0	0
	4-Nov-04	0.8712907	305600	48	-4.3	0.000000	85	0	0
	4-Nov-06	0.8712907	305600	31	-5.4	0.000000	90	0	0
	4-Nov-08	0.8712907	305600	31	-1.3	0.000000	89	0	0
	4-Nov-09	0.8712907	305600	44	-3.9	0.000000	88	0	0
Quebec	6-Jun-05	0.7362097	305600	33	17	0.000120	87	0	1
	6-Jun-92	0.7362097	305600	37	22	0.000100	95	1	0
	6-Jun-93	0.7362097	305600	32	21.5	0.000000	99	0	0
	6-Jun-94	0.7362097	305600	48	27	0.000407	87	1	0
	6-Jun-95	0.73620972	305600	46	19.4	0.00031481	93	1	0
	6-Jun-96	0.7362097	305600	43	23.9	0.000000	81	0	0
	6-Jun-97	0.7362097	305600	31	14.2	0.000000	95	0	0
	6-Jun-98	0.7362097	305600	31	13.7	0.000000	98	0	0
	6-Jun-01	0.7362097	305600	31	13.4	0.000067	100	0	0
	6-Jun-02	0.7362097	305600	35	16.4	0.000000	94	0	0
	6-Jun-03	0.7362097	305600	48	17.9	0.000230	95	1	0
	6-Jun-04	0.7362097	305600	41	22.5	0.000000	79	0	0
	6-Jun-06	0.7362097	305600	31	20	0.000000	89	0	0
	6-Jun-07	0.7362097	305600	31	24.8	0.000000	98	0	0
Quebec	19-Jul-05	0.7853632	305600	31	33.5	0.000000	94	0	1

	19-Jul-92	0.7853632	305600	31	22.8	0.000000	97	0	0
	19-Jul-93	0.7853632	305600	33	19.2	0.000000	90	0	0
	19-Jul-94	0.7853632	305600	31	23.4	0.000111	96	1	0
	19-Jul-96	0.7853632	305600	46	16.3	0.001236	92	0	0
	19-Jul-97	0.7853632	305600	39	19.3	0.000000	100	0	0
	19-Jul-98	0.7853632	305600	50	26.3	0.000000	91	0	0
	19-Jul-99	0.7853632	305600	52	25.8	0.001083	97	1	0
	19-Jul-00	0.78536319	305600	39	24.2	0.00037963	100	1	0
	19-Jul-01	0.7853632	305600	31	28.9	0.000000	92	0	0
	19-Jul-03	0.7853632	305600	31	23.9	0.000593	97	1	0
	19-Jul-04	0.7853632	305600	31	18.9	0.000078	97	1	0
	19-Jul-06	0.7853632	305600	31	25.7	0.000000	95	0	0
	19-Jul-07	0.7853632	305600	31	23.7	0.000157	96	1	0
Quebec	1-Aug-93	0.7760786	305600	31	25.4	0.000000	100	0	0
	1-Aug-94	0.7760786	305600	32	29.1	0.000000	100	0	0
	1-Aug-95	0.7760786	305600	31	31.5	0.001074	97	1	0
	1-Aug-96	0.7760786	305600	31	23.5	0.000078	84	1	0
	1-Aug-97	0.7760786	305600	56	27.1	0.000111	100	1	0
	1-Aug-98	0.7760786	305600	31	23.6	0.000000	100	0	0
	1-Aug-00	0.7760786	305600	31	28.7	0.000000	97	0	0
	1-Aug-01	0.7760786	305600	31	28.4	0.000000	91	0	0
	1-Aug-03	0.7760786	305600	31	27.8	0.000000	97	0	0
	1-Aug-04	0.7760786	305600	80	29.5	0.001204	94	1	0
	1-Aug-06	0.7760786	305600	33	22.6	0.000000	97	0	0
	1-Aug-07	0.7760786	305600	31	23.5	0.000000	93	0	0
	1-Aug-	0.77607865	305600	39	18.8	0.00030556	91	1	0

	08								
	1-Aug-09	0.7760786	305600	31	27.1	0.000000	86	0	0
Quebec	9-Aug-05	0.7760786	305600	52	34.1	0.000000	96	0	1
	9-Aug-92	0.7760786	305600	37	28.4	0.000000	99	0	0
	9-Aug-94	0.7760786	305600	31	23.9	0.000000	97	0	0
	9-Aug-95	0.7760786	305600	31	33.1	0.000000	95	0	0
	9-Aug-96	0.7760786	305600	31	28	0.000067	81	1	0
	9-Aug-97	0.7760786	305600	31	29.1	0.000000	100	0	0
	9-Aug-98	0.7760786	305600	31	32.9	0.000000	100	0	0
	9-Aug-99	0.7760786	305600	39	17.8	0.000155	98	1	0
	9-Aug-00	0.7760786	305600	31	18.7	0.000290	97	1	0
	9-Aug-02	0.7760786	305600	32	22.2	0.000000	85	0	0
	9-Aug-03	0.7760786	305600	31	19.3	0.000111	97	1	0
	9-Aug-04	0.7760786	305600	31	19.8	0.001667	95	1	0
	9-Aug-06	0.7760786	305600	31	23.7	0.000000	91	0	0
	9-Aug-07	0.7760786	305600	52	21	0.000340	100	1	0
	9-Aug-09	0.7760786	305600	31	25.1	0.000000	90	0	0
Quebec	10-Aug-92	0.7760786	305600	31	25.6	0.000000	88	0	0
	10-Aug-93	0.77607865	305600	31	24.9	0.00101852	100	1	0
	10-Aug-94	0.7760786	305600	31	22.6	0.000000	97	0	0
	10-Aug-95	0.7760786	305600	31	28.7	0.000000	97	0	0
	10-Aug-96	0.7760786	305600	31	26.6	0.000000	81	0	0
	10-Aug-97	0.7760786	305600	31	21.2	0.000000	100	0	0
	10-Aug-98	0.7760786	305600	31	33.4	0.000000	87	0	0
	10-Aug-99	0.7760786	305600	41	19.9	0.000000	76	0	0
	10-Aug-00	0.7760786	305600	31	16.7	0.000396	98	0	0

	10-Aug-02	0.7760786	305600	32	23.3	0.000000	93	0	0
	10-Aug-05	0.7760786	305600	31	25.9	0.000130	94	1	0
	10-Aug-07	0.7760786	305600	31	26.7	0.000000	90	0	0
	10-Aug-08	0.7760786	305600	31	19.3	0.000000	91	0	0
	10-Aug-09	0.7760786	305600	31	19.6	0.000183	98	1	0
Quebec	26-Aug-03	0.7760786	305600	31	19.6	0.000000	91	0	1
	26-Aug-92	0.7760786	305600	31	17	0.000500	94	0	0
	26-Aug-94	0.7760786	305600	31	24.4	0.000000	95	0	0
	26-Aug-95	0.7760786	305600	31	15.3	0.000000	91	0	0
	26-Aug-96	0.7760786	305600	46	20.2	0.000000	68	0	0
	26-Aug-97	0.77607865	305600	31	18.6	0.00038889	100	1	0
	26-Aug-98	0.7760786	305600	31	15.3	0.000142	100	0	0
	26-Aug-99	0.7760786	305600	31	25.7	0.000000	95	0	0
	26-Aug-02	0.7760786	305600	31	23.4	0.000155	96	1	0
	26-Aug-04	0.7760786	305600	31	25.5	0.000000	99	0	0
	26-Aug-05	0.7760786	305600	37	27.1	0.000000	90	0	0
	26-Aug-06	0.7760786	305600	31	17.4	0.000000	98	0	0
	26-Aug-08	0.7760786	305600	31	20.5	0.000000	77	0	0
	26-Aug-09	0.7760786	305600	56	26.6	0.000000	81	0	0
Quebec	26-Dec-03	0.9583106	305600	31	-2	0.000256	98	0	1
	26-Dec-93	0.9583106	305600	44	-7.6	0.000171	94	0	0
	26-Dec-94	0.9583106	305600	56	-6.1	0.000014	75	0	0
	26-Dec-95	0.9583106	305600	31	0.7	0.000074	100	0	0
	26-Dec-96	0.9583106	305600	37	-16.6	0.000000	76	0	0
	26-Dec-97	0.9583106	305600	31	-0.7	0.000065	100	0	0
	26-Dec-	0.9583106	305600	31	-22.7	0.000000	77	0	0

	98								
	26-Dec-99	0.9583106	305600	31	-11.7	0.000000	86	0	0
	26-Dec-00	0.9583106	305600	41	-13.4	0.000038	91	0	0
	26-Dec-02	0.95831058	305600	50	-7.1	1.6908E-05	85	0	0
	26-Dec-05	0.9583106	305600	41	-7.9	0.000271	93	0	0
	26-Dec-06	0.9583106	305600	31	-6.4	0.000050	88	0	0
	26-Dec-07	0.9583106	305600	35	-9.3	0.000000	86	0	0
Quebec	26-Dec-09	0.9583106	305600	31	-12	0.000000	90	0	0
	26-Dec-08	0.9583106	305600	31	-22.8	0.000000	75	0	0
Quebec	2-Aug-02	0.7760786	305600	31	22.4	0.000250	97	1	1
	2-Aug-92	0.7760786	305600	41	21.1	0.000074	95	1	0
	2-Aug-93	0.7760786	305600	31	25.2	0.000000	100	0	0
	2-Aug-95	0.7760786	305600	31	21.4	0.000130	97	1	0
	2-Aug-98	0.7760786	305600	46	27.8	0.000102	97	1	0
	2-Aug-99	0.7760786	305600	31	23.8	0.000000	96	0	0
	2-Aug-00	0.7760786	305600	33	24.8	0.000178	95	1	0
	2-Aug-01	0.7760786	305600	32	31	0.000000	84	0	0
	2-Aug-03	0.7760786	305600	31	25.8	0.000000	96	0	0
	2-Aug-04	0.7760786	305600	35	26.2	0.000000	94	0	0
	2-Aug-05	0.7760786	305600	31	19	0.000000	97	0	0
	2-Aug-06	0.7760786	305600	37	27.4	0.000000	86	0	0
	2-Aug-07	0.77607865	305600	31	19.8	0.00048611	96	1	0
	2-Aug-08	0.7760786	305600	33	17.3	0.000083	90	1	0
Quebec	14-Aug-92	0.7760786	305600	31	20.1	0.000000	97	0	0
	14-Aug-93	0.7760786	305600	31	21.3	0.000014	100	1	0
	14-Aug-94	0.7760786	305600	50	23.9	0.000111	91	1	0

	14-Aug-95	0.7760786	305600	31	19.9	0.000000	100	0	0
	14-Aug-96	0.7760786	305600	31	23.6	0.000000	80	0	0
	14-Aug-97	0.7760786	305600	31	15.9	0.000049	100	0	0
	14-Aug-99	0.7760786	305600	37	22.7	0.000382	98	1	0
	14-Aug-00	0.7760786	305600	31	24.4	0.000000	99	0	0
	14-Aug-01	0.7760786	305600	69	25	0.000000	99	0	0
	14-Aug-03	0.7760786	305600	37	24.1	0.000000	79	0	0
	14-Aug-04	0.7760786	305600	31	25.6	0.000167	93	1	0
	14-Aug-05	0.7760786	305600	31	22.6	0.000000	84	0	0
	14-Aug-06	0.7760786	305600	33	23.9	0.000056	87	1	0
	14-Aug-07	0.7760786	305600	31	19.7	0.000000	95	0	0
	14-Aug-09	0.7760786	305600	31	30.8	0.000056	94	1	0
Quebec	8-Sep-02	0.7225560	305600	33	7.7	0.000419	96	0	1
	8-Sep-92	0.72255598	305600	31	21.5	0.00011111	94	1	0
	8-Sep-93	0.7225560	305600	31	20.9	0.000000	100	0	0
	8-Sep-94	0.7225560	305600	31	20.3	0.000028	100	1	0
	8-Sep-95	0.7225560	305600	37	22.7	0.000101	96	1	0
	8-Sep-96	0.7225560	305600	31	21.4	0.000000	79	0	0
	8-Sep-97	0.7225560	305600	31	20	0.000000	100	0	0
	8-Sep-98	0.7225560	305600	31	15.8	0.000063	97	0	0
	8-Sep-00	0.7225560	305600	44	7.7	0.000000	95	0	0
	8-Sep-01	0.7225560	305600	31	12.2	0.000000	97	0	0
	8-Sep-03	0.7225560	305600	33	6	0.000000	82	0	0
	8-Sep-05	0.7225560	305600	31	25.6	0.000000	83	0	0
	8-Sep-06	0.7225560	305600	33	25.6	0.000000	99	0	0
	8-Sep-08	0.7225560	305600	31	19.7	0.000201	100	1	0
	8-Sep-09	0.7225560	305600	31	20	0.000000	95	0	0
Quebec	7-Nov-02	0.8712907	305600	52	-6.9	0.000042	90	0	1
	7-Nov-92	0.8712907	305600	30	-10.8	0.000006	87	0	0
Quebec	7-Nov-94	0.8712907	305600	83	1.8	0.000107	100	0	0
	7-Nov-95	0.8712907	305600	50	-5.8	0.000611	96	0	0
	7-Nov-	0.87129073	305600	41	-6.8	0.00014444	73	0	0

	96								
	7-Nov-97	0.8712907	305600	31	-6.8	0.000000	100	0	0
	7-Nov-98	0.8712907	305600	31	-2.4	0.000000	90	0	0
	7-Nov-99	0.8712907	305600	31	-1.6	0.000000	89	0	0
	7-Nov-00	0.8712907	305600	31	4.8	0.000017	99	0	0
	7-Nov-03	0.8712907	305600	31	-6.6	0.000000	92	0	0
	7-Nov-04	0.8712907	305600	31	-2.4	0.000048	95	0	0
	7-Nov-05	0.8712907	305600	54	2.6	0.000296	97	0	0
	7-Nov-06	0.8712907	305600	35	-8.6	0.000000	92	0	0
	7-Nov-07	0.8712907	305600	56	-2.5	0.000575	95	0	0
	7-Nov-08	0.8712907	305600	31	2	0.000130	97	0	0
Quebec	11-Jun-92	0.7362097	305600	31	18.4	0.000000	93	0	0
	11-Jun-93	0.7362097	305600	31	16	0.000000	97	0	0
	11-Jun-94	0.7362097	305600	54	29	0.000000	97	0	0
	11-Jun-95	0.7362097	305600	31	13.9	0.000222	95	0	0
	11-Jun-96	0.7362097	305600	41	27.2	0.000000	82	0	0
	11-Jun-97	0.7362097	305600	37	19.7	0.000000	81	0	0
	11-Jun-98	0.7362097	305600	31	27.2	0.000000	98	0	0
	11-Jun-99	0.73620972	305600	31	27.1	0	93	0	0
	11-Jun-02	0.7362097	305600	31	15.6	0.001167	97	0	0
	11-Jun-03	0.7362097	305600	35	21.1	0.000292	98	1	0
	11-Jun-04	0.7362097	305600	52	14.8	0.000000	64	0	0
	11-Jun-05	0.7362097	305600	31	21.8	0.000000	83	0	0
	11-Jun-06	0.7362097	305600	31	15.2	0.000395	98	0	0
	11-Jun-07	0.7362097	305600	31	24.5	0.000000	100	0	0
	21-Jul-01	0.7853632	305600	31	33.5	0.000022	94	1	1

	21-Jul-92	0.7853632	305600	37	24.2	0.000250	90	1	0
Quebec	21-Jul-94	0.7853632	305600	41	29.8	0.000630	95	1	0
	21-Jul-96	0.7853632	305600	31	18.2	0.000423	85	1	0
	21-Jul-97	0.7853632	305600	32	18.3	0.000028	84	1	0
	21-Jul-98	0.7853632	305600	31	25.2	0.000000	97	0	0
	21-Jul-99	0.7853632	305600	32	26.6	0.000000	81	0	0
	21-Jul-00	0.7853632	305600	31	19.2	0.000167	94	1	0
	21-Jul-02	0.7853632	305600	41	28.3	0.000000	89	0	0
	21-Jul-03	0.7853632	305600	31	21.5	0.000071	97	1	0
	21-Jul-05	0.7853632	305600	31	28.4	0.000000	89	0	0
	21-Jul-06	0.78536319	305600	31	24.5	5.5556E-05	96	1	0
	21-Jul-07	0.7853632	305600	31	22.8	0.000074	93	1	0
	21-Jul-08	0.7853632	305600	31	20.5	0.000306	91	1	0
	21-Jul-09	0.7853632	305600	35	25.1	0.000000	96	0	0
Quebec	22-Jul-01	0.7853632	305600	31	20	0.000028	97	1	1
	22-Jul-92	0.7853632	305600	31	19.4	0.000000	96	0	0
	22-Jul-93	0.7853632	305600	31	17.6	0.000333	100	1	0
	22-Jul-95	0.7853632	305600	35	24.1	0.000000	100	0	0
	22-Jul-96	0.7853632	305600	33	17.1	0.000000	82	0	0
	22-Jul-97	0.7853632	305600	31	17.6	0.000000	89	0	0
	22-Jul-98	0.7853632	305600	46	27.5	0.000689	100	1	0
	22-Jul-99	0.7853632	305600	31	26.1	0.000167	99	1	0
	22-Jul-00	0.7853632	305600	31	22.9	0.000296	98	1	0
	22-Jul-02	0.7853632	305600	44	31.4	0.000056	89	1	0
	22-Jul-03	0.7853632	305600	31	18.6	0.000194	95	1	0
	22-Jul-	0.7853632	305600	39	29.4	0.000000	96	0	0

	04								
	22-Jul-05	0.7853632	305600	31	27.1	0.000278	96	1	0
	22-Jul-06	0.7853632	305600	31	26.7	0.000000	97	0	0
	22-Jul-07	0.78536319	305600	31	25.2	0	93	0	0
	22-Jul-08	0.7853632	305600	31	22.8	0.000100	91	1	0
	22-Jul-09	0.7853632	305600	31	18.2	0.000154	98	1	0
Quebec	24-Jul-01	0.7853632	305600	41	30.4	0.000375	97	1	1
	24-Jul-92	0.7853632	305600	31	26.4	0.000000	100	0	0
	24-Jul-93	0.7853632	305600	31	14.7	0.000063	94	0	0
	24-Jul-94	0.7853632	305600	31	28.5	0.000896	100	1	0
	24-Jul-95	0.7853632	305600	31	26	0.001117	100	1	0
	24-Jul-96	0.7853632	305600	31	24.8	0.000000	83	0	0
	24-Jul-97	0.7853632	305600	35	28.8	0.000000	100	0	0
	24-Jul-98	0.7853632	305600	31	24.9	0.000046	97	1	0
	24-Jul-99	0.7853632	305600	37	23.9	0.000000	98	0	0
	24-Jul-00	0.7853632	305600	31	20.7	0.000000	100	0	0
	24-Jul-02	0.7853632	305600	31	20.7	0.000000	93	0	0
	24-Jul-04	0.7853632	305600	32	21.4	0.000587	92	1	0
	24-Jul-05	0.7853632	305600	44	22.8	0.000000	72	0	0
	24-Jul-06	0.7853632	305600	31	23.8	0.000000	97	0	0
	24-Jul-07	0.7853632	305600	32	30.8	0.000000	96	0	0
	24-Jul-08	0.78536319	305600	31	21.7	0	90	0	0
	24-Jul-09	0.7853632	305600	31	26.7	0.000000	98	0	0
Quebec	10-Jul-00	0.7853632	305600	37	21.8	0.000354	100	1	1
	10-Jul-92	0.7853632	305600	31	15.4	0.000187	99	0	0
	10-Jul-93	0.7853632	305600	31	21.8	0.000204	97	1	0

	10-Jul-94	0.7853632	305600	31	26.4	0.000694	89	1	0
	10-Jul-95	0.7853632	305600	31	24.7	0.000000	97	0	0
	10-Jul-96	0.7853632	305600	31	23.1	0.000574	89	1	0
Quebec	10-Jul-97	0.7853632	305600	31	17.3	0.000000	100	0	0
	10-Jul-98	0.7853632	305600	31	16.2	0.000319	100	0	0
	10-Jul-99	0.7853632	305600	31	19.1	0.000022	96	1	0
	10-Jul-01	0.7853632	305600	31	20.9	0.000024	97	1	0
	10-Jul-02	0.7853632	305600	35	20.7	0.000000	85	0	0
	10-Jul-03	0.7853632	305600	48	24.5	0.000000	64	0	0
	10-Jul-05	0.7853632	305600	31	23.8	0.000000	92	0	0
	10-Jul-06	0.7853632	305600	31	19.1	0.000032	96	1	0
	10-Jul-07	0.7853632	305600	31	16.8	0.000128	97	0	0
	10-Jul-08	0.7853632	305600	31	24.7	0.000685	93	1	0
	10-Jul-09	0.78536319	305600	31	26.9	0	93	0	0
Quebec	17-Jul-00	0.7853632	305600	31	17.1	0.000444	100	1	1
	17-Jul-92	0.7853632	305600	32	20.3	0.000000	89	0	0
	17-Jul-93	0.7853632	305600	37	11.8	0.000116	95	0	0
	17-Jul-94	0.7853632	305600	31	20.8	0.000000	99	0	0
	17-Jul-95	0.7853632	305600	31	18.5	0.000000	97	0	0
	17-Jul-97	0.7853632	305600	41	24.6	0.000528	100	1	0
	17-Jul-98	0.7853632	305600	32	24.2	0.000630	100	1	0
Quebec	17-Jul-99	0.7853632	305600	39	33.7	0.000000	85	0	0
	17-Jul-01	0.7853632	305600	31	22.2	0.000000	100	0	0
	17-Jul-02	0.7853632	305600	33	26.5	0.000000	100	0	0
	17-Jul-03	0.7853632	305600	31	27.1	0.000000	94	0	0
	17-Jul-	0.7853632	305600	33	24.1	0.000000	95	0	0

	04								
	17-Jul-05	0.7853632	305600	31	27.8	0.000000	95	0	0
	17-Jul-06	0.7853632	305600	31	25.5	0.000306	100	1	0
	17-Jul-09	0.7853632	305600	31	19.4	0.000167	100	1	0
Quebec	6-Jan-98	1.0000000	305600	31	-20	0.000028	80	0	1
	6-Jan-92	1.0000000	305600	31	-1.2	0.000395	100	0	0
	6-Jan-93	1	305600	31	-19.8	0	91	0	0
	6-Jan-94	1.0000000	305600	65	-18.5	0.000000	80	0	0
	6-Jan-95	1.0000000	305600	41	-24.6	0.000000	71	0	0
	6-Jan-96	1.0000000	305600	31	-24.1	0.000000	89	0	0
	6-Jan-97	1.0000000	305600	31	-12.3	0.000014	84	0	0
	6-Jan-99	1.0000000	305600	52	-20	0.000118	93	0	0
	6-Jan-00	1.0000000	305600	31	-10.1	0.000000	88	0	0
	6-Jan-01	1.0000000	305600	33	-6.5	0.000169	97	0	0
	6-Jan-02	1.0000000	305600	31	-18.2	0.000028	91	0	0
	6-Jan-03	1.0000000	305600	31	-17.6	0.000000	91	0	0
	6-Jan-04	1.0000000	305600	31	-11	0.000056	87	0	0
	6-Jan-05	1.0000000	305600	31	-23.5	0.000000	71	0	0
	6-Jan-06	1.0000000	305600	31	-11.5	0.000035	100	0	0
	6-Jan-07	1.0000000	305600	31	-1	0.000134	97	0	0
	6-Jan-08	1.0000000	305600	39	-10.5	0.000083	92	0	0
	6-Jan-09	1.0000000	305600	59	-14.3	0.000000	61	0	0
Quebec	4-Dec-97	0.9583106	305600	37	0.9	0.000167	98	0	1
	4-Dec-92	0.9583106	305600	46	-2.6	0.000038	89	0	0
	4-Dec-93	0.95831058	305600	31	-4.2	0	100	0	0
	4-Dec-95	0.9583106	305600	31	-14.1	0.000048	100	0	0
	4-Dec-96	0.9583106	305600	31	-2.2	0.000000	97	0	0
	4-Dec-98	0.9583106	305600	41	-9	0.000125	96	0	0
	4-Dec-99	0.9583106	305600	31	-9	0.000000	97	0	0
	4-Dec-00	0.9583106	305600	31	-16.1	0.000000	99	0	0
	4-Dec-01	0.9583106	305600	32	-10	0.000000	97	0	0
	4-Dec-02	0.9583106	305600	50	-17.1	0.000000	81	0	0
	4-Dec-03	0.9583106	305600	39	-6.8	0.000059	90	0	0

	4-Dec-04	0.9583106	305600	61	-12.1	0.000458	99	0	0
	4-Dec-05	0.9583106	305600	50	1.5	0.000538	97	0	0
	4-Dec-06	0.9583106	305600	32	-4.3	0.000225	91	0	0
	4-Dec-07	0.9583106	305600	50	-7.1	0.000000	77	0	0
Quebec	7-Dec-97	0.9583106	305600	31	-1.3	0.000130	100	0	1
	7-Dec-93	0.9583106	305600	31	-11.7	0.000038	94	0	0
	7-Dec-95	0.9583106	305600	32	-19.7	0.000000	91	0	0
	7-Dec-96	0.9583106	305600	31	-1.7	0.000003	93	0	0
	7-Dec-98	0.9583106	305600	70	-3.4	0.000235	100	0	0
	7-Dec-99	0.95831058	305600	31	-1.1	0.00014052	95	0	0
	7-Dec-00	0.9583106	305600	31	-15.1	0.000000	86	0	0
	7-Dec-02	0.9583106	305600	41	-20.4	0.000000	82	0	0
	7-Dec-03	0.9583106	305600	50	-5	0.000006	81	0	0
	7-Dec-04	0.9583106	305600	31	-16.4	0.000000	76	0	0
	7-Dec-05	0.9583106	305600	37	-10.1	0.000000	70	0	0
	7-Dec-06	0.9583106	305600	31	-3.5	0.000000	94	0	0
	7-Dec-07	0.9583106	305600	31	-20.4	0.000074	89	0	0
	7-Dec-08	0.9583106	305600	31	-7.2	0.000042	94	0	0
Quebec	2-Nov-92	0.8712907	305600	31	-7.8	0.000000	85	0	0
Quebec	2-Nov-09	0.8712907	305600	31	-4.3	0.000000	86	0	0
	2-Nov-94	0.8712907	305600	32	5.3	0.000386	100	0	0
	2-Nov-95	0.8712907	305600	31	-7.9	0.000167	99	0	0
	2-Nov-96	0.8712907	305600	31	-7.3	0.000000	74	0	0
	2-Nov-97	0.8712907	305600	37	2.5	0.000496	100	0	0
	2-Nov-98	0.8712907	305600	31	4.4	0.000194	100	0	0
	2-Nov-	0.8712907	305600	56	14.8	0.000000	90	0	0

	99								
	2-Nov-00	0.8712907	305600	31	0.9	0.000000	89	0	0
	2-Nov-01	0.87129073	305600	31	6.2	0	91	0	0
	2-Nov-02	0.8712907	305600	41	-4.6	0.000211	94	0	0
	2-Nov-03	0.8712907	305600	37	-4	0.000000	82	0	0
	2-Nov-04	0.8712907	305600	31	-0.6	0.000278	94	0	0
	2-Nov-05	0.8712907	305600	50	11.3	0.000000	94	0	0
	2-Nov-06	0.8712907	305600	31	-4	0.000000	96	0	0
	2-Nov-07	0.8712907	305600	46	-6.1	0.000000	87	0	0
	2-Nov-08	0.8712907	305600	41	-4.2	0.000019	86	0	0

Quebec Dataset I – Test Data

Province	Date	Consumption Index	Network Size (km)	Wind (km/hr.)	Temperature (Celsius)	Precipitation (mm/s)	Relative Humidity (%)	Lightning	PNN Model Predicted Outputs
Quebec	4-Nov-07	0.8712907	305600	61	-0.5	0.001366	97	0	0.99
Quebec	4-Nov-94	0.8712907	305600	31	-2.2	0.000000	94	0	0.079
Quebec	6-Jun-	0.7362097	305600	32	20.5	0.000000	87	0	0.105

	08								
Quebec	6-Jun-09	0.7362097	305600	35	23.9	0.000296	91	1	0.039
Quebec	19-Jul-02	0.7853632	305600	31	19.8	0.000000	94	0	0.08
Quebec	19-Jul-09	0.7853632	305600	31	24.1	0.000148	100	1	0.032
Quebec	1-Aug-05	0.7760786	305600	31	19.6	0.000100	95	1	0.979
Quebec	9-Aug-01	0.7760786	305600	31	29.9	0.000537	96	1	0.071
Quebec	39669	0.776078646	305600	31	20.1	0	90	0	0.04
Quebec	10-Aug-03	0.7760786	305600	31	21.1	0.000151	97	1	0.928
Quebec	26-Aug-01	0.7760786	305600	46	27.1	0.000122	99	1	0.055
Quebec	26-Dec-01	0.9583106	305600	31	-5	0.000000	95	0	0.044
Quebec	2-Aug-94	0.7760786	305600	31	20.9	0.000083	92	1	0.016
Quebec	2-Aug-09	0.7760786	305600	31	26.8	0.000000	91	0	0.077
Quebec	14-Aug-02	0.7760786	305600	31	28.5	0.000000	97	0	0.993
Quebec	14-Aug-08	0.7760786	305600	31	19.6	0.000000	89	0	0.036
Quebec	8-Sep-07	0.7225560	305600	33	30.4	0.000000	96	0	0.056
Quebec	37508	0.72255598	305600	31	30.3	0	90	0	0.953
Quebec	9-Sep-92	0.7225560	305600	31	16.3	0.000000	87	0	0.084
Quebec	7-Nov-93	0.8712907	305600	32	-6.7	0.000000	90	0	0.1
Quebec	7-Nov-09	0.8712907	305600	31	-5.8	0.000167	76	0	0.019
Quebec	11-Jun-01	0.7362097	305600	31	23.2	0.000000	90	0	0.925
Quebec	11-Jun-00	0.7362097	305600	31	15.1	0.000000	85	0	0.104
Quebec	22-Jul-94	0.7853632	305600	31	28.1	0.000194	96	1	0.01
Quebec	4-Dec-94	0.9583106	305600	59	-6.3	0.000059	97	0	0.03
Quebec	4-Dec-08	0.9583106	305600	48	-1.4	0.000000	91	0	0.091
Quebec	40151	0.958310577	305600	57	-7.3	0	75	0	0.065
Quebec	2-Nov-93	0.8712907	305600	46	-6.5	0.000239	98	0	0.934
Quebec	7-Dec-09	0.9583106	305600	33	-9.8	0.000000	80	0	0.007
Quebec	2-Aug-96	0.7760786	305600	31	20.6	0.000000	82	0	0.002
Quebec	26-Aug-07	0.7760786	305600	31	21.9	0.000651	96	1	0.089
Quebec	19-Jul-08	0.7853632	305600	31	25.1	0.000000	92	0	0.029

Quebec	1-Aug-92	0.7760786	305600	48	12.8	0.000579	99	0	0.055
Quebec	6-Jun-99	0.7362097	305600	48	24.1	0.000194	94	1	0.029
Quebec	4-Nov-05	0.8712907	305600	41	-3.1	0.000000	79	0	0.105
Quebec	36683	0.736209721	305600	44	18.6	0	96	0	0.091
Quebec	19-Jul-95	0.7853632	305600	31	24.6	0.000144	100	1	0.098
Quebec	1-Aug-02	0.7760786	305600	31	20.8	0.000000	95	0	0.093
Quebec	10-Aug-06	0.7760786	305600	31	21	0.000056	94	1	0.032
Quebec	26-Dec-04	0.9583106	305600	31	-21.9	0.000111	71	0	0.1
Quebec	11-Jun-08	0.7362097	305600	31	23.5	0.000472	92	1	0.063
Quebec	2-Aug-97	0.7760786	305600	31	21.5	0.000398	100	1	0.08
Quebec	14-Aug-98	0.7760786	305600	31	23.5	0.000000	100	0	0.001
Quebec	8-Sep-04	0.7225560	305600	31	7.1	0.000167	90	0	0.043
Quebec	37202	0.871290734	305600	82	1.3	6.7901E-05	93	0	0.082
Quebec	11-Jun-09	0.7362097	305600	31	12	0.000025	95	0	0.095
Quebec	21-Jul-95	0.7853632	305600	31	22.6	0.000083	100	1	0.071
Quebec	10-Jul-04	0.7853632	305600	31	15.1	0.000014	91	0	0.04
Quebec	17-Jul-08	0.7853632	305600	32	26.8	0.000133	91	1	0.073
Quebec	24-Jul-03	0.7853632	305600	31	22.2	0.000175	97	1	0.053
Quebec	2-Nov-91	0.8712907	305600	31	3.6	0.000293	100	0	0.093

APPENDIX II

GENERAL CODE FOR MATLAB

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created 19-Oct-2015 22:06:29
%
% This script assumes these variables are defined:
%
%   x - input data.
%   y - target data.

x = x';
t = y';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainbr';  % Bayesian Regularization  backpropagation.

% Create a Fitting Network
hiddenLayerSize = 15;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);
```

```
% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
    % Generate MATLAB function for neural network for application
    % deployment in MATLAB scripts or with MATLAB Compiler and Builder
    % tools, or simply to examine the calculations your trained neural
    % network performs.
    genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a matrix-only MATLAB function for neural network code
    % generation with MATLAB Coder tools.
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment with.
    % Simulink Coder tools.
    gensim(net);
end
```

BPNN MODEL CODES FOR MATLAB

Fitting Network

```
function out1 = fitnet(varargin)
%FITNET Function fitting neural network.
%
%  For an introduction use the Neural Fitting App <a href="matlab: doc
nftool">nftool</a>.
%  Click <a href="matlab:nftool">here</a> to launch it.
%
%  Two (or more) layer fitting networks can fit any finite input-output
%  relationship arbitrarily well given enough hidden neurons.
%
%  <a href="matlab:doc fitnet">fitnet</a>(hiddenSizes,trainFcn) takes a row
vector of N hidden layer
%  sizes, and a backpropagation training function, and returns
%  a feed-forward neural network with N+1 layers.
%
%  Input, output and output layers sizes are set to 0.  These sizes will
%  automatically be configured to match particular data by <a
href="matlab:doc train">train</a>. Or the
%  user can manually configure inputs and outputs with <a href="matlab:doc
configure">configure</a>.
%
%  Defaults are used if <a href="matlab:doc fitnet">fitnet</a> is called
with fewer arguments.
%  The default arguments are (10,'<a href="matlab:doc
trainlm">trainlm</a>').
%
%  Here a fitting network is used to solve a simple fitting problem:
%
%    [x,t] = <a href="matlab:doc simplefit_dataset">simplefit_dataset</a>;
%    net = <a href="matlab:doc fitnet">fitnet</a>(10);
%    net = <a href="matlab:doc train">train</a>(net,x,t);
%    <a href="matlab:doc view">view</a>(net)
%    y = net(x);
%    perf = <a href="matlab:doc perform">perform</a>(net,t,y)
%
%  See also FEEDFORWARDNET, PATTERNNET.

% Mark Beale, 2008-13-2008
% Copyright 2008-2011 The MathWorks, Inc.

%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Network Functions.

  persistent INFO;
  if isempty(INFO), INFO = get_info; end
  if (nargin > 0) && ischar(varargin{1}) ...
      && ~strcmpi(varargin{1},'hardlim') &&
~strcmpi(varargin{1},'hardlims')
    code = varargin{1};
    switch code
```

```
      case 'info',
        out1 = INFO;
      case 'check_param'
        err = check_param(varargin{2});
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = err;
      case 'create'
        if nargin < 2, error(message('nnet:Args:NotEnough')); end
        param = varargin{2};
        err = nntest.param(INFO.parameters,param);
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = create_network(param);
        out1.name = INFO.name;
      otherwise,
        % Quick info field access
        try
          out1 = eval(['INFO.' code]);
        catch %#ok<CTCH>
          nnerr.throw(['Unrecognized argument: ''' code ''''])
        end
    end
  else
    [args,param] = nnparam.extract_param(varargin,INFO.defaultParam);
    [param,err] = INFO.overrideStructure(param,args);
    if ~isempty(err), nnerr.throw('Args',err,'Parameters'); end
    net = create_network(param);
    net.name = INFO.name;
    out1 = init(net);
  end
end

function v = fcnversion
  v = 7;
end

%  BOILERPLATE_END
%% =======================================================

function info = get_info
  info = nnfcnNetwork(mfilename,'Function Fitting Neural
Network',fcnversion, ...
    [ ...
    nnetParamInfo('hiddenSizes','Hidden Layer
Sizes','nntype.strict_pos_int_row',10,...
    'Sizes of 0 or more hidden layers.'), ...
    nnetParamInfo('trainFcn','Training
Function','nntype.training_fcn','trainlm',...
    'Function to train the network.'), ...
    ]);
end

function err = check_param(param)
  err = '';
end

function net = create_network(param)
```

```
  net = feedforwardnet(param.hiddenSizes,param.trainFcn);
  net.plotFcns = [net.plotFcns {'plotfit'}];
end
```

Bayesian Regularization

```
function [out1,out2] = trainbr(varargin)
%TRAINBR Bayesian Regularization backpropagation.
%
%  <a href="matlab:doc trainbr">trainbr</a> is a network training function
that updates the weight and
%  bias values according to Levenberg-Marquardt optimization.  It
%  minimizes a combination of squared errors and weights
%  and, then determines the correct combination so as to produce a
%  network which generalizes well.  The process is called Bayesian
%  regularization.
%
%  [NET,TR] = <a href="matlab:doc trainbr">trainbr</a>(NET,X,T,Xi,Ai,EW)
takes additional optional
%  arguments suitable for training dynamic networks and training with
%  error weights.  Xi and Ai are the initial input and layer delays states
%  respectively and EW defines error weights used to indicate
%  the relative importance of each target value.
%
%  Training occurs according to training parameters, with default values.
%  Any or all of these can be overridden with parameter name/value argument
%  pairs appended to the input argument list, or by appending a structure
%  argument with fields having one or more of these names.
%    epochs            1000  Maximum number of epochs to train
%    goal                 0  Performance goal
%    mu               0.005  Marquardt adjustment parameter
%    mu_dec             0.1  Decrease factor for mu
%    mu_inc              10  Increase factor for mu
%    mu_max            1e10  Maximum value for mu
%    max_fail             0  Maximum validation failures
%    min_grad          1e-7  Minimum performance gradient
%    show                25  Epochs between displays
%    showCommandLine  false  Generate command-line output
%    showWindow        true  Show training GUI
%    time               inf  Maximum time to train in seconds
%
%  Validation stops are disabled by default (max_fail = 0) so that
%  training can continue until an optimial combination of errors and
%  weights are found.  However, some weight/bias minimization can still
%  be achieved with shorter training times if validation is enabled
%  (by setting max_fail to 6 or some other strictly positive value).
%
%  To make this the default training function for a network, and view
%  and/or change parameter settings, use these two properties:
%
%    net.<a href="matlab:doc nnproperty.net_trainFcn">trainFcn</a> =
'trainbr';
%    net.<a href="matlab:doc nnproperty.net_trainParam">trainParam</a>
%
%  See also TRAINGDM, TRAINGDA, TRAINGDX, TRAINLM, TRAINRP,
```

```
%           TRAINCGF, TRAINCGB, TRAINSCG, TRAINCGP, TRAINBFG.

% Copyright 1992-2014 The MathWorks, Inc.


%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Training Functions.

persistent INFO;
if isempty(INFO)
    INFO = get_info;
end
nnassert.minargs(nargin,1);
in1 = varargin{1};
if ischar(in1)
    switch (in1)
        case 'info'
            out1 = INFO;
        case 'apply'
            [out1,out2] = train_network(varargin{2:end});
        case 'formatNet'
            out1 = formatNet(varargin{2});
        case 'check_param'
            param = varargin{2};
            err = nntest.param(INFO.parameters,param);
            if isempty(err)
                err = check_param(param);
            end
            if nargout > 0
                out1 = err;
            elseif ~isempty(err)
                nnerr.throw('Type',err);
            end
        otherwise,
            try
                out1 = eval(['INFO.' in1]);
            catch me, nnerr.throw(['Unrecognized first argument: ''' in1
''''])
            end
    end
else
    net = varargin{1};
    oldTrainFcn = net.trainFcn;
    oldTrainParam = net.trainParam;
    if ~strcmp(net.trainFcn,mfilename)
        net.trainFcn = mfilename;
        net.trainParam = INFO.defaultParam;
    end
    [out1,out2] = train(net,varargin{2:end});
    net.trainFcn = oldTrainFcn;
    net.trainParam = oldTrainParam;
end
end

%  BOILERPLATE_END
```

```
%% ==========================================================

function info = get_info()
isSupervised = true;
usesGradient = false;
usesJacobian = true;
usesValidation = true;
supportsCalcModes = true;
info = nnfcnTraining(mfilename,'Bayesian Regularization',8.0,...

isSupervised,usesGradient,usesJacobian,usesValidation,supportsCalcModes,...
    [ ...
    nnetParamInfo('showWindow','Show Training Window
Feedback','nntype.bool_scalar',true,...
    'Display training window during training.'), ...
    nnetParamInfo('showCommandLine','Show Command Line
Feedback','nntype.bool_scalar',false,...
    'Generate command line output during training.') ...
    nnetParamInfo('show','Command Line
Frequency','nntype.strict_pos_int_inf_scalar',25,...
    'Frequency to update command line.'), ...
    ...
    nnetParamInfo('epochs','Maximum Epochs','nntype.pos_scalar',1000,...
    'Maximum number of training iterations before training is stopped.')
...
    nnetParamInfo('time','Maximum Training
Time','nntype.pos_inf_scalar',inf,...
    'Maximum time in seconds before training is stopped.') ...
    ...
    nnetParamInfo('goal','Performance Goal','nntype.pos_scalar',0,...
    'Performance goal.') ...
    nnetParamInfo('min_grad','Minimum Gradient','nntype.pos_scalar',1e-
7,...
    'Minimum performance gradient before training is stopped.') ...
    nnetParamInfo('max_fail','Maximum Validation
Checks','nntype.pos_int_scalar',0,...
    'Maximum number of validation checks before training is stopped.') ...
    ...
    nnetParamInfo('mu','Mu','nntype.strict_pos_scalar',0.005,...
    'Mu.'), ...
    nnetParamInfo('mu_dec','Mu Decrease
Ratio','nntype.strict_pos_scalar',0.1,...
    'Ratio to decrease mu.'), ...
    nnetParamInfo('mu_inc','Mu Increase
Ratio','nntype.strict_pos_scalar',10,...
    'Ratio to increase mu.'), ...
    nnetParamInfo('mu_max','Maximum mu','nntype.strict_pos_scalar',1e10,...
    'Maximum mu before training is stopped.'), ...
    ], ...
    [ ...
    nntraining.state_info('gradient','Gradient','continuous','log') ...
    nntraining.state_info('mu','Mu','continuous','log') ...
    nntraining.state_info('gamk','Num Parameters','continuous','linear')
...
    nntraining.state_info('ssX','Sum Squared Param','continuous','log') ...
    nntraining.state_info('val_fail','Validation
Checks','discrete','linear') ...
```

```
    ]);
end

function err = check_param(param)
err = '';
end

function net = formatNet(net)
if isempty(net.performFcn)
    warning(message('nnet:train:EmptyPerformanceFixed'));
    net.performFcn = 'mse';
end
if isempty(nnstring.first_match(net.performFcn,{'sse','mse'}))
    warning(message('nnet:train:NonSqrErrorFixed'));
    net.performFcn = 'mse';
end
if isfield(net.performParam,'regularization')
    if net.performParam.regularization ~= 0
        disp([nnlink.fcn2ulink('trainbr') ': '
nnwarning.adaptive_reg_override])
        net.performParam.regression = 0;
    end
end
end

function [archNet,tr] = train_network(archNet,rawData,calcLib,calcNet,tr)
[archNet,tr] =
nnet.train.trainNetwork(archNet,rawData,calcLib,calcNet,tr,localfunctions);
end

function worker = initializeTraining(archNet,calcLib,calcNet,tr)

% Cross worker existence required
worker.WB = [];

% Initial Gradient
[worker.xsE,worker.vperf,worker.tperf,worker.je,worker.jj,...
    worker.xgradient,worker.trainN] = calcLib.perfsJEJJ(calcNet);

if calcLib.isMainWorker

    % Training control values
    worker.epoch = 0;
    worker.startTime = clock;
    worker.param = archNet.trainParam;
    worker.originalNet = calcNet;
    [worker.best,worker.val_fail] =
nntraining.validation_start(calcNet,worker.xsE,worker.vperf);

    worker.WB = calcLib.getwb(calcNet);
    worker.length_X = numel(worker.WB);

    worker.ii =
sparse(1:worker.length_X,1:worker.length_X,ones(1,worker.length_X));
    worker.mu = worker.param.mu;
```

```
    worker.numParameters = worker.length_X;
    worker.gamk = worker.numParameters;
    if worker.xsE == 0
        worker.beta = 1;
    else
        worker.beta = (worker.trainN - worker.gamk)/(2 * worker.xsE);
    end
    if (worker.beta <=0)
        worker.beta = 1;
    end
    worker.ssX = worker.WB' * worker.WB;
    worker.alph = worker.gamk / (2 * worker.ssX);
    worker.perf = worker.beta * worker.xsE + worker.alph * worker.ssX;

    % Training Record
    worker.tr = nnet.trainingRecord.start(tr,worker.param.goal,...

{'epoch','time','perf','vperf','tperf','mu','gradient','gamk','ssX','val_fa
il'});

    % Status
    worker.status = ...
        [ ...

nntraining.status('Epoch','iterations','linear','discrete',0,worker.param.e
pochs,0), ...

nntraining.status('Time','seconds','linear','discrete',0,worker.param.time,
0), ...

nntraining.status('Performance','','log','continuous',worker.xsE,worker.par
am.goal,worker.xsE) ...

nntraining.status('Gradient','','log','continuous',worker.xgradient,worker.
param.min_grad,worker.xgradient) ...

nntraining.status('Mu','','log','continuous',worker.mu,worker.param.mu_max,
worker.mu) ...
        nntraining.status('Effective #
Param','','linear','continuous',worker.gamk,0,worker.gamk) ...
        nntraining.status('Sum Squared
Param','','log','continuous',worker.ssX,0,worker.ssX) ... ...
        nntraining.status('Validation
Checks','','linear','discrete',0,worker.param.max_fail,0) ...
        ];
end
end

function [worker,calcNet] = updateTrainingState(worker,calcNet)

% Stopping Criteria
current_time = etime(clock,worker.startTime);
[userStop,userCancel] =  nntraintool('check');
if userStop
    worker.tr.stop = message('nnet:trainingStop:UserStop');
```

```
    calcNet = worker.best.net;
elseif userCancel
    worker.tr.stop = message('nnet:trainingStop:UserCancel');
    calcNet = worker.originalNet;
elseif (worker.xsE <= worker.param.goal)
    worker.tr.stop = message('nnet:trainingStop:PerformanceGoalMet');
    calcNet = worker.best.net;
elseif (worker.epoch == worker.param.epochs)
    worker.tr.stop = message('nnet:trainingStop:MaximumEpochReached');
    calcNet = worker.best.net;
elseif (current_time >= worker.param.time)
    worker.tr.stop = message('nnet:trainingStop:MaximumTimeElapsed');
    calcNet = worker.best.net;
elseif (worker.xgradient <= worker.param.min_grad)
    worker.tr.stop = message('nnet:trainingStop:MinimumGradientReached');
    calcNet = worker.best.net;
elseif (worker.mu >= worker.param.mu_max)
    worker.tr.stop = message('nnet:trainingStop:MaximumMuReached');
    calcNet = worker.best.net;
elseif (worker.val_fail >= worker.param.max_fail) && (worker.param.max_fail
> 0)
    worker.tr.stop = message('nnet:trainingStop:ValidationStop');
    calcNet = worker.best.net;
end

% Training Record
worker.tr = nnet.trainingRecord.update(worker.tr, ...
    [worker.epoch current_time worker.xsE worker.vperf worker.tperf
worker.mu ...
    worker.xgradient worker.gamk worker.ssX worker.val_fail]);
worker.statusValues = ...

[worker.epoch,current_time,worker.xsE,worker.xgradient,worker.mu,worker.gam
k,worker.ssX,worker.val_fail];
end

function [worker,calcNet] = trainingIteration(worker,calcLib,calcNet)

% Cross worker control variables
worker.muBreak = [];
worker.perfBreak = [];
worker.WB2 = [];

% Bayesian Regularization
while true
    if calcLib.isMainWorker
        worker.muBreak = (worker.mu > worker.param.mu_max);
    end
    if calcLib.broadcast(worker.muBreak)
        break;
    end

    if calcLib.isMainWorker

        [dX,flag_inv] = computeDX(worker);
```

```
        worker.WB2 = worker.WB + dX;
        ssX2 = worker.WB2' * worker.WB2;
    end

    calcNet2 = calcLib.setwb(calcNet,worker.WB2);
    xsE2 = calcLib.trainPerf(calcNet2);

    if calcLib.isMainWorker
        perf2 = worker.beta * xsE2 + worker.alph * ssX2;
    end

    if calcLib.isMainWorker
        worker.perfBreak = (perf2 < worker.perf) && all(isfinite(dX)) &&
flag_inv;
    end
    if calcLib.broadcast(worker.perfBreak)
        if calcLib.isMainWorker
            [worker.WB,worker.ssX,worker.perf] =
deal(worker.WB2,ssX2,perf2);
        end
        calcNet = calcLib.setwb(calcNet,worker.WB2);
        if calcLib.isMainWorker
            worker.mu = worker.mu * worker.param.mu_dec;
            if (worker.mu < 1e-20)
                worker.mu = 1e-20;
            end
        end
        break
    end
    if calcLib.isMainWorker
        worker.mu = worker.mu * worker.param.mu_inc;
    end
end
[worker.xsE,worker.vperf,worker.tperf,worker.je,worker.jj,worker.xgradient]
= ...
    calcLib.perfsJEJJ(calcNet);

if calcLib.isMainWorker
    if (worker.mu <= worker.param.mu_max)
        % Update regularization parameters and performance function
        warnstate = warning('off','all');
        worker.gamk = worker.numParameters - worker.alph *
trace(inv(worker.beta * worker.jj + worker.ii * worker.alph));
        warning(warnstate);
        if (worker.ssX == 0)
            worker.alph = 1;
        else
            worker.alph = worker.gamk / (2 * worker.ssX);
        end
        if (worker.xsE == 0)
            worker.beta = 1;
        else
            worker.beta = (worker.trainN - worker.gamk)/( 2* worker.xsE);
        end
        worker.perf = worker.beta * worker.xsE + worker.alph * worker.ssX;
```

```
    end

    % Track Best Network
    [worker.best,worker.tr,worker.val_fail] =
nnet.train.trackBestNetwork(...

worker.best,worker.tr,worker.val_fail,calcNet,worker.xsE,worker.vperf,worke
r.epoch);
end
end

function [dX,flag_inv] = computeDX(worker)

% Check for Singular Matrix warnings
[msgstr,msgid] = lastwarn;
lastwarn('MATLAB:nothing','MATLAB:nothing') % Save lastwarn state
warnstate = warning('off','all'); % Suppress warnings

num = -(worker.beta * worker.jj + worker.ii * (worker.mu + worker.alph));
den = (worker.beta * worker.je + worker.alph * worker.WB);
dX = num \ den;

[~,msgid1] = lastwarn;
flag_inv = isequal(msgid1,'MATLAB:nothing');
if flag_inv
    lastwarn(msgstr,msgid);
end; % Restore lastwarn state
warning(warnstate); % Restore warnings
end
```

GRNN MODEL CODES FOR MATLAB

```
function out1 = newgrnn(varargin)
%NEWGRNN Design a generalized regression neural network.
%
%  Generalized regression neural networks are a kind
%  of radial basis network that is often used for function
%  approximation.  GRNNs can be designed very quickly.
%
%  <a href="matlab:doc newgrnn">newgrnn</a>(X,T,SPREAD) takes RxQ matrix of
column input vectors,
%  SxQ matrix of column target vectors, and the SPREAD of the radial
%  basis functions (default = 1.0), and returns a new generalized
%  regression network.
%
%  The larger SPREAD is, the smoother the function approximation
%  will be.  To fit data closely, use a SPREAD smaller than the
%  typical distance between input vectors.  To fit the data more
%  smoothly use a larger SPREAD.
%
%  Here a radial basis network is designed from inputs X and targets T,
%  and simulated.
%
%    x = [1 2 3];
%    t = [2.0 4.1 5.9];
%    net = <a href="matlab:doc newgrnn">newgrnn</a>(x,t);
%    y = net(x)
%
%  See also SIM, NEWRB, NEWGRNN, NEWPNN.

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%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Network Functions.

  persistent INFO;
  if isempty(INFO), INFO = get_info; end
  if (nargin > 0) && ischar(varargin{1}) ...
      && ~strcmpi(varargin{1},'hardlim') &&
~strcmpi(varargin{1},'hardlims')
    code = varargin{1};
    switch code
      case 'info',
        out1 = INFO;
      case 'check_param'
        err = check_param(varargin{2});
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = err;
      case 'create'
        if nargin < 2, error(message('nnet:Args:NotEnough')); end
        param = varargin{2};
        err = nntest.param(INFO.parameters,param);
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = create_network(param);
```

```
        out1.name = INFO.name;
      otherwise,
        % Quick info field access
        try
          out1 = eval(['INFO.' code]);
        catch %#ok<CTCH>
          nnerr.throw(['Unrecognized argument: ''' code ''''])
        end
    end
  else
    [args,param] = nnparam.extract_param(varargin,INFO.defaultParam);
    [param,err] = INFO.overrideStructure(param,args);
    if ~isempty(err), nnerr.throw('Args',err,'Parameters'); end
    net = create_network(param);
    net.name = INFO.name;
    out1 = init(net);
  end
end

function v = fcnversion
  v = 7;
end

%  BOILERPLATE_END
%% =======================================================

function info = get_info
  info = nnfcnNetwork(mfilename,'Generalized Regression Neural
Network',fcnversion, ...
    [ ...
    nnetParamInfo('inputs','Input Data','nntype.data',{},...
    'Input data.'), ...
    nnetParamInfo('targets','Target Data','nntype.data',{},...
    'Target output data.'), ...
    nnetParamInfo('spread','Radial basis
spread','nntype.strict_pos_scalar',1,...
    'Distance from radial basis center to 0.5 output.'), ...
    ]);
end

function err = check_param(param)
  err = '';
end

%%
function net = create_network(param)

  % Data
  p = param.inputs;
  t = param.targets;
  if iscell(p), p = cell2mat(p); end
  if iscell(t), t = cell2mat(t); end

  % Dimensions
  [R,Q] = size(p);
```

```
  [S,Q] = size(t);

  % Architecture
  net = network(1,2,[1;0],[1;0],[0 0;1 0],[0 1]);

  % Simulation
  net.inputs{1}.size = R;
  net.layers{1}.size = Q;
  net.inputWeights{1,1}.weightFcn = 'dist';
  net.layers{1}.netInputFcn = 'netprod';
  net.layers{1}.transferFcn = 'radbasn';
  net.layers{2}.size = S;
  net.layerWeights{2,1}.weightFcn = 'dotprod';

  % Weight and Bias Values
  net.b{1} = zeros(Q,1)+sqrt(-log(.5))/param.spread;
  net.iw{1,1} = p';
  net.lw{2,1} = t;
end
```

PNN MODEL CODES FOR MATLAB

```
function out1 = newpnn(varargin)
%NEWPNN Design a probabilistic neural network.
%
%  Probabilistic neural networks are a kind of radial
%  basis network suitable for classification problems.
%
%  <a href="matlab:doc newpnn">newpnn</a>(P,T,SPREAD) takes an RxQ input
matrix P and an SxQ target matrix
%  T, a radial basis function SPREAD and returns a new probabilistic
%  neural network.
%
%  If SPREAD is near zero the network will act as a nearest
%  neighbor classifier.  As SPREAD becomes larger the designed
%  network will take into account several nearby design vectors.
%
%  Here a classification problem is defined with a set of
%  inputs P and class indices Tc.  A PNN is designed to fit this data.
%
%    P = [1 2 3 4 5 6 7];
%    Tc = [1 2 3 2 2 3 1];
%    T = <a href="matlab:doc ind2vec">ind2vec</a>(Tc)
%    net = <a href="matlab:doc newpnn">newpnn</a>(P,T);
%    Y = net(P)
%    Yc = <a href="matlab:doc vec2ind">vec2ind</a>(Y)
%
%  See also SIM, IND2VEC, VEC2IND, NEWRB, NEWRBE, NEWGRNN.

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%% =======================================================
%  BOILERPLATE_START
%  This code is the same for all Network Functions.

  persistent INFO;
  if isempty(INFO), INFO = get_info; end
  if (nargin > 0) && ischar(varargin{1}) ...
      && ~strcmpi(varargin{1},'hardlim') &&
~strcmpi(varargin{1},'hardlims')
    code = varargin{1};
    switch code
      case 'info',
        out1 = INFO;
      case 'check_param'
        err = check_param(varargin{2});
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = err;
      case 'create'
        if nargin < 2, error(message('nnet:Args:NotEnough')); end
        param = varargin{2};
        err = nntest.param(INFO.parameters,param);
        if ~isempty(err), nnerr.throw('Args',err); end
        out1 = create_network(param);
        out1.name = INFO.name;
```

```
      otherwise,
        % Quick info field access
        try
          out1 = eval(['INFO.' code]);
        catch %#ok<CTCH>
          nnerr.throw(['Unrecognized argument: ''' code ''''])
        end
    end
  else
    [args,param] = nnparam.extract_param(varargin,INFO.defaultParam);
    [param,err] = INFO.overrideStructure(param,args);
    if ~isempty(err), nnerr.throw('Args',err,'Parameters'); end
    net = create_network(param);
    net.name = INFO.name;
    out1 = init(net);
  end
end

function v = fcnversion
  v = 7;
end

%  BOILERPLATE_END
%% =======================================================

function info = get_info
  info = nnfcnNetwork(mfilename,'Probabilistic Neural Network',fcnversion,
...
    [ ...
    nnetParamInfo('inputs','Input Data','nntype.data',{},...
    'Input data.'), ...
    nnetParamInfo('targets','Target Data','nntype.data',{},...
    'Target output data.'), ...
    nnetParamInfo('spread','Radial basis
spread','nntype.strict_pos_scalar',0.1,...
    'Distance from radial basis center to 0.5 output.'), ...
    ]);
end

function err = check_param(param)
  err = '';
end

function net = create_network(param)

% Data
  p = param.inputs;
  t = param.targets;
  if iscell(p), p = cell2mat(p); end
  if iscell(t), t = cell2mat(t); end

  % Dimensions
  [R,Q] = size(p);
  [S,Q] = size(t);
```

```
  % Architecture
  net = network(1,2,[1;0],[1;0],[0 0;1 0],[0 1]);

  % Simulation
  net.inputs{1}.size = R;
  net.inputWeights{1,1}.weightFcn = 'dist';
  net.layers{1}.netInputFcn = 'netprod';
  net.layers{1}.transferFcn = 'radbas';
  net.layers{1}.size = Q;
  net.layers{2}.size = S;
  net.layers{2}.transferFcn = 'compet';
  net.outputs{2}.exampleOutput = t;

  % Weight and Bias Values
  net.b{1} = zeros(Q,1)+sqrt(-log(.5))/param.spread;
  net.iw{1,1} = p';
  net.lw{2,1} = t;
end
```